Exploring the Impact of Business Intelligence (BI) Use on Organisational Power Dynamics: A National Health Service (NHS) Case Study

Kamran Ahmed MAHROOF

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Abstract

Kamran Mahroof

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Key words: Business Intelligence, Technology Enactment, Power Dynamics, National Health Service, Public Sector, Data Analysts

The public sector, particularly healthcare organisations are under ever increasing pressure to do more with less. This coupled with the need to keep up to the constant technological changes and ever increasing abundance of information has led to many public sector organisations adopting Business Intelligence (BI) in order to leverage business value and improve decision-making. However, many organisations such as the National Health Service (NHS) continue to fail in their Information Technology (IT) related initiatives. While the rise of BI and its growing influence in organisations has attracted much academic attention, this has largely been from architectural, design and technological perspectives, whilst little is known about how BI is used by various organisational actors to reach decisions, nor much is understood regarding its resulting impact on organisational power dynamics.

Thus, there remains an under researched area of discussion in the literature from the perspective of BI users. While studies report how BI can impact organisational effectiveness, facilitate data driven decision making and supposedly overcome intuitive decision making, the extent to which BI impacts and alters power dynamics between organisational actors across the organisation has received little attention. Accordingly, this research adopts a qualitative case study approach to explore power resulting from BI use within a large NHS trust by conducting 30 semi-structured interviews consisting of operational managers and BI analysts. Through taking a human-centric approach, this research uncovers how BI is altering power dynamics between organisational actors, whereby BI analysts are becoming increasingly

influential as a result of their analytical skills. It was found that operational managers are becoming more reliant upon data analysts, resulting in the analysts having more and more influence. However, this research finds it is only when the analysts supplement their technical skill-set with their institutional knowledge, that they have the ability to influence and enact power within the organisational settings. The research also offers insights into the contestations and conflicts which arise from the use of BI, between operational managers and analysts as well as between in-house analysts, based in the operation setting and the centralised analysts, operating across the entire trust. Accordingly, this research empirically validates a BI Power Enactment Framework and proposes the BI Power Matrix, which may assist policy makers in identifying determining key factors which are contributory to the success or failure of technological initiatives.

Dedication

First and foremost, all praise to God Almighty for allowing me to overcome many challenges and for giving me the strength and determination to successfully complete my PhD studies. This is for my beloved parents, who have prayed day and night for my success, for my lovely wife for all her patience and understanding and for my beautiful daughter, Hafsa Iman, who kept me distracted, yet determined during my studies.

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List of abbreviations

BD	Big Data
BI	Business Intelligence
CCG	Clinical Commissioning Groups
CI	Competitive intelligence
CIO	Chief Information officers
CSU	Clinical Service Units
CTO	Chief Technology officers
DM	Data mining
DSS	Decision support system
DW	Data warehouse
EIS	Executive Information Systems
eRS	e-Referral Service
IS	Information System
IT	Information Technology
ICT	Information and Communication Technology
KM	Knowledge management
KMS	Knowledge management systems
MI	Market intelligence
MIS	Management information systems
NHS	National Health Service
OLAP	Online analytical processing
TEF	The Technology Enactment Framework

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1.0 CHAPTER 1: Introduction

1.1 Introduction

The recent rise in radical computational power, expotential data capturing capabilities and unprecedented development in deep neural networks has led to technologies such as Artificial intelligence (AI) to be considered as the most disruptive class of technologies for the coming few decades, with it expected to contribute up to $15.7 trillion to the global economy by 2030, with $6.6 trillion attributed to increased productivity, whereas the remaining $9.1 trillion expected to come from consumption-side effects (PwC 2019). Such techolonogies have the abililty to enable organisations to harness data in a way not previously seen, allowing them to adapt to new situations and solve problems beyond current capabilities (Gartner 2017a). Despite the rise in technological trends such as Big data analytics and AI, BI systems continue to be widely used in many areas of business that entails making decisions to create value (Trieu 2017). Business intelligence systems are advantaged by a rise in sensing opportunities as witnessed in both the number of sensors and the rich diversity of sensors ranging from cell phones, personal computers, and health tracking appliances to Internet of Things (IoT) technologies designed to give contextual, semantic voice to entities that previously could not contribute intelligence to key decisions.

Despite other technological advancements, BI adoption continues to rise, indicating that BI is still largely viewed as a de facto tool for organisational effectiveness. Yet, in the face of such investments, and despite substantial increased attention from within the public sector in recent times, many organisations fail to fully leverage value from their BI investments. A key challenge relating to this can be attributed to approaches to decision-making, as reflected in the extant literature, whereby one stream of academic studies emphasis the managerial reliance on information in their decision-making process, while conversely, other management studies maintain that business decisions are regularly executed based on gut feelings and intuitions, thus

overlooking parts, or on occasions, all the available data and information (Delen et al. 2018). Therefore, further insights into the human aspect of BI are required to best understand how it is used and what impact is has between organisational actors.

1.2 Research Background

The International Data Corporation (IDC) (2012) has estimated that organisations will generate and store forty exabytes of data by 2020. Therefore, unsurprisingly according to leading Technology and Research company, Gartner (2017), worldwide BI and analytics market is expected to grow to $22.8 billion by the end of 2020, with BI spending compared to overall IT budget continuing to rise, thus indicating the valuable insights BI is seen as achieving for organisations. In the face of technological advancements such as AI, Big Data, Machine Learning and IoT, an underlying reason as to why BI remains highly relevant and a popular option in current times is due to organisations being able to use it without IT assistance and the analytical offering at enterprise levels (Gartner 2017b). As a result, BI remains a growing interest in academia, whilst also being relevant in industry (Ramakrishnan et al.,2012; Trieu 2017).

However, BI more recently has attracted much interest among public organisations, particularly in the last few years (Henkel et al., 2017). There is an underlying notion, given the nature and context of public sector organisations, that in order for BI and analytics to be successful, it should be aligned with public organisations' goals and their ways of working (Klievink et al., 2017). This too is evident in the case of the National Health Service (NHS), who are also transitioning towards a data-driven environment, with the aim of transforming patient care through the effective use of BI (Wachter 2016).

According to Cavanillas et al. (2016), attention to the potential of data is key for public sector organisations, particularly given the enormous amounts of data produced as a result of daily operations such as tax and pension remittance, invoicing and healthcare reporting. A logical response of public

organisations towards their data rich environments is to harness technologies such as BI to effectively support decision-making. Particularly given that an increasing number of organisations are opting for BI due to its perceived impact on business performance (Hawking and Sellitto, 2010). As such, BI success is considered imperative to the organisations which invest in technology (Gaardboe 2018). The tangible benefits attained by organisations in the private sector has prompted policymakers to consider the benefits of technologies such as BI and analytics within the public sector (ICO 2016). Local governments are increasingly experimenting with BI technologies with the aim of reducing operating costs through rearranging services (Symons, 2016).

The field of BI covers a wide range of areas, not only relevant to organisations many internal operations, but also its external environments, such as competitors and the marketplace (Love 2007). Nonetheless, the core, underlying idea of BI is not new and has historical roots (Kinsinger 2007). For instance, previous civilisations have developed methods for collecting and analysing intelligence for decision support, particularly in the context of battles, wars and diplomacy. Additionally, Calof and Wright (2008) posit that ancient military organisations indulged in industrial espionage, whereby they established methods to collect and develop intelligence of other organisations. The concept and way in which intelligence is used has continued to evolve, with intelligence driven insights now applied largely by organisations in the marketplace. However, in order for organisations to benefit from such intelligence driven insights, the need for valuable and timely information is necessary. Similarly, organisations also require competent decision makers, who possess the relevant skills to interpret, acknowledge and utilise the various BI technologies and tools.

Therefore, researching a phenomenon that has gained global popularity, attracted immense attention, large scale investment and which seemingly profitably impacts business practices is a rational and viable field to research. However, the business value stemming from such investments are not necessarily responsible for the first-hand benefits attained by organisations.

Rather, it is reported that such assets in combination with human capabilities are key in achieving business successes, which can lead to overall business value (Devraj and Kohli 2003), therefore indicating that human factors are both an important and timely discussion within BI use.

1.2.1 Context: Business Intelligence Development

Data is now being utilised in almost every area of business operations, leading to a situation whereby collecting, storing and analysing data is no longer a choice for organisations, but a vital requirement. Much of this has been made possible due to how IT is being used, shifting from merely processing activities through to providing organisations with intelligence and values insights. As a result, organisations are moving from traditional techniques of processing data and interpretation to more advanced forms such as BI systems to meet their information needs (Tunowski 2015). However, in order to appreciate the technical development and growth of BI, revisiting the timeline by approximately 60 years is sufficient. Particularly as the history of BI is rich and its provenance can be traced 50 years ago during the 1950's which saw the advent of mainframe computers, triggering the earliest forms of data processing systems. Although the underlying mechanics of the systems did not change, the power and capabilities of these systems have. Then, organisations regardless of size and scope were seemingly well-acquainted and dependent on non-automated means of operations.

This is in contrast to today's reliance on the various forms of technologies, systems and analytical tools that organisations utilise. Prior to the era of computerised operations, although decisions were data driven, organisations had fewer analysing options therefore resulting in more intuitive decision making. The subsequent rise of computational power presented organisations with increased storage, processing and eventually analytical capabilities which overcame limitations associated with solely human decision making (Maule, 2010). Previous literature has argued that IT investments such as BI fail to directly lead to business success, rather organisational benefits are attained through collaboration of the technology and human capabilities (Aral and Weill

2007, Deveraj and Kholi 2003). Therefore, exploring how much, if any of this intuitiveness is lost with the advent of smart, complex technology is a highly relevant yet surprisingly unreached point of discussion within the BI context.

The rise in data processing systems led to the spread of the Management Information Systems (MIS), designed to support decision-making at managerial levels. The prospering relationship between hardware, software and communications led to unforeseen advancements in the field of IS (Buchholtz et al. 2014). Although Dresner, a Gartner analyst is often recognised for the term BI (Watson and Wixom 2007), it was during this period that Peter Luhn, an IBM researcher coined the term BI during the latter 1950's, referring to it as '*the ability to apprehend the interrelationships of presented facts in such a way as to guide way as to guide action towards a desired goal'* (Luhn, 1958: 314). This was in reference to managing the growth of literature in both of these respective fields. The 1960's saw further technological advancements leading to the arrival of the mini computers, which in turn, similar to the preceding decade initiated the era of decision support systems (DSS) and group support systems (GSS) alike (Nunamaker 1989). From within this initial techno-cycle of development and movement, facilitating the decision-making process can be seen as the incumbent, central underpinning of these technological advancements. Gorry and Scott-Morton (1971) and Arnott and Pervan (2005) emphasis the drawbacks of the outputs produced by the standardised MIS. Though data was being extrapolated in the seemingly novel form of periodic reports (as never before), they offered limited options for managerial decision making. In order to overcome this void, and to facilitate organisational managers with the interactive ability to aid decision-making, DSS and GSS were introduced and put in place to allow collaborative semi-structured and unstructured decision-making.

Although DSS were designed and developed for all personnel of the organisation, the DSS was extensively utilised by managerial staff at the lower and middle rankings (Watson et al. 1991). The computing support continually evolved over the decades, supporting activities in various areas of the organisation. However, executives of organisations did not benefit from DSS

as initially expected. While these systems were intended to support the higher personnel of the organisations too, they failed to fully achieve this. Nevertheless this changed following the sequential process, of new improved systems arising from technological advancements which further ensued in the 1970's with the advents of the relational databases (Codd 1970; Astrahan et al. 1976). The relational model allowed for capturing larger quantities of data, in the process facilitating more superior modelling abilities ultimately leading to the onset of the Executive Information Systems (EIS) (Arnott and Pervan 2005). Consequently, the lack of support for senior personnel was overcome with the rise of EIS (Main 1989). These systems offered seamless access of both internal and external information for their decision-making requirements (Petrini and Pozzebon 2009), therefore placing 'key information on the desktops of executives' (Rasmussen et al. 2002: 99). Although the systems gained popularity following the influx of Data Warehousing (DW) and Online Analytical Processing tools (OLAP) (Inmon 1992).

Following the period of earlier advancements, IS and knowledge acquisition formed a closer bond, in the form of Knowledge Management Systems (KMS). The emergence of KMS can be partially attributed to the unforeseen requirement for organisations to retain knowledge (Galliers and Newell 2001), which was being depleted following managerial redundancies at the time as a result of organisational downsizing in the form business process engineering (Davenport 1995). Therefore, it can be suggested that IS has progressively tailored systems for the decision-maker with the advent of EIS and KMS, offering organisational decision makers with increased personalisation and decision-making flexibility. Shollo and Galliers (2016) highlight the evolution of IS in support of managerial decision making, by emphasising previous systems being standardised and reactive to more personalised and proactive in their orientation.

The developments in IS attracted much academic attention. Arnott and Pervan (2005) highlight that IS research was heavily focused on personal DSS and GSS between the period 1990 -2003. However, the 'hype-and-failure publishing cycle' described by Watson (2015) was witnessed to some extent

by the late 1980's, particularly in relation to these earlier IS developments. Both DSS (Carlsson and Turban, 2002) and EIS (Volonino et al., 1995) gained attention from researchers, leading to flourishing research in these areas for approximately two decades. However their subsequent influences and impacts in practise continued to decline. Much of this was as a result of the reported high maintenance of EIS systems which required large amounts of manual work when converting and loading data from data sources, whilst on the other hand, DSS was seen as having somewhat of a narrow scope (Petrini and Pozzebon 2009). Watson (2015) posits new technologies and applications in particular will continue to undergo this form of hype and failure publishing cycle. It was therefore not till pertinent technological developments by the late 1990's in the form of DW (Inmon 1996), Extraction, Transformation and Loading tools (Body et al. 2002) and OLAP (Gonzalez 2014) that saw the rise of BI.

Over the course of 50 years, the technological advancements from the earlier systems such as MIS to the contemporary BI systems highlight a gradual increase in decision making abilities for its users (Arnott 2004). This is further witnessed by the early 2000's with the arrival of the internet, which played a major role in supporting IS development. The internet has been a major contributor and obvious enabler to the expansion and drive of BI, allowing analytical tools to be used in the most flexible manner yet, from various locations, even away from the office (Carlsson and Turban 2002). Its rise and incorporation within BI systems had also profoundly impacted decision-making within the organisational setting. Hossack et al. (2012) outlines the arrival and use of the internet, incorporated with an array of DSS's allowed operational workers within the organisation to access more data for analysing purposes, therefore increasing the decision-making responsibilities lower down in the organisational hierarchy. Thus, the evolution of decision support technology over the years has seen a shift from mass produced reactive systems, to more interactive, proactive systems.

1.3 Research Problem and Rationale

Despite other technological advancements, BI adoption continues to rise, indicating that BI is still largely viewed as a de facto tool for organisational effectiveness. Yet, in the face of such investments, and despite substantial increased attention from within the public sector in recent times, many organisations fail to fully leverage value from their BI investments. A key challenge relating to this can be attributed to approaches to decision-making, as reflected in the extant literature, whereby one stream of academic studies emphasis the managerial reliance on information in their decision-making process, while conversely, other management studies maintain that business decisions are regularly executed based on gut feelings and intuitions, thus overlooking parts, or on occasions, all the available data and information (Delen et al. 2018).

An initial review of the extant BI literature indicates that studies have been largely focused on architectural, design and the technologies that support BI (Chan et al., 2018), BI cloud design (Sangupamba et al. 2016), critical success factors (Isik et al., 2013; Olszak 2016), BI performance (Vallurupalli and Bose 2018; Torres et al. 2018) thus largely at the consequence of 'human' factors related to BI. This has led to a lack of insights into how organisational actors utilise BI for decision making purposes, thus past studies have outlined that the manifestation of technology in organisation studies is scarce (Orlikowski, 1992; Orlikowski and Iacono, 2001), and exploring the interplay between technology and actors remains a key challenge (Karanasios 2018).

Furthermore, while BI implementation in general has achieved much benefit across various fields such as Retailing (Banerjee and Mishra 2017), Banking (Moro et al. 2015), Manufacturing (Yusof et al. 2013), Tourism (Vajirakachorn and Chongwatpol 2017) and even the Fashion industry (Acharya et al. 2018), it has been more problematic for the healthcare sector (Foshay and Kuziemsky 2014). This is unsurprising, given that failures and only fractional successes are common in technology-supported innovation programmes within health

and social care (Greenhalgh et al. 2018). It is widely reported that much of this is largely attributed to high complexity (Cortada et al. 2012; Wang and Liao 2008) information, process factors and especially human factors (Foshay and Kuziemsky, 2014) pertaining to organisational culture/change management (Augustsson et al. 2019; Ileri and Arik 2018; Nizar et al. 2010; Al-Moosa and Sharts-Hopko 2016; Batra and Pall 2015, Cresswell and Sheikh 2013) as well as people skills (Howard et al. 2015; Gordon et al. 2015; Sisodia & Agarwal 2017; Raghupathi & Raghupathi 2014; Meyer, 2019; Konttila et al. 2019; Ariyachandra and Frolick, 2008, Geiger, 2009, Yeoh and Koronios, 2009, Yeoh et al., 2008).

Previous studies have emphasised the complications associated with introducing large-scale IT into the public sector (Willcocks & Currie, 1997), particularly in healthcare given that multiple stakeholders hold varying positions of power and influence, which can sometimes derail IT projects (Boonstra et al., 2008; Currie, 2012). Thus, exploring the Impact of technology on power should be a key focus, given that power is not a stable resource, as it moves between actants such as politicians, healthcare organisations like the NHS, suppliers and the public (Mark 2007). Therefore, despite the extant literature acknowledging (though loosely), human related challenges such as skills, change management and technology adoption, there is a dearth of studies which specifically explores the impact of BI use on organsational power dynamics, especially within public sector organisations from the context of healthcare.

In addition, there is a general consensus in the field that the organisational and human factors have contributed to the success or failure of many IT projects, more than the technical ones (Justinia 2017). A prime example of such failure is the case of the National Programme for Information Technology (NPfIT) in the NHS in the UK, which ended abruptly as *'the worst and most expensive contracting fiascos in public institution history'* (Syal, 2013).

However, such large scale failures have been ineffective in that it was unable to deter the NHS from pursuing its digital transformation agenda; to continue, the NHS has embarked on several large scale projects, such as the electronic-

online system, ‘choose and book’ (CAB) later rebadged as eRS and more recently The Digital Challenge to achieve a *Paperless NHS by 2020*. Sceptics argued if studies fail to address the underlying challenges previously witnessed, that such systems too would inevitably face the same fate as NPfIT (Peckham, 2016). For instance, Pouloudi et al. (2016) posit the failure of NPfIT was not attributed as a "computer failure" (as propagated by the media) but rather due to conflicted stakeholder positions and stakes that conspired to destabilise the original government health IT policy.

Therefore, human factors and the power dynamics were seen to pay a significant role in such failures. Thus, the inherently top-down culture of the NHS, which is underpinned by autocratic management is reported to create a host of problems across the NHS as a network (Smyth 2018). Accordingly, the apparent need for NPfIT was also essentially driven by political need and desire rather than a clinical or public one (Brennan 2007), leading to conflicting priorities and dissonance. It is due to these factors which have provided the motivation for this exploratory study from a human-centric perspective. In order to address this and the shortcomings in the extant literature, it is important to consider the human factors associated with BI decision making, whilst focusing on organisational power dynamics.

Accordingly, the case context for this research, the NHS, provides further impetus for this research, given that the organisation, similar to their previous aspirations and attempts, is undergoing a digitisation programme, in which they are strategising to operate ‘*Paperless by 2020’* (NHS choice 2018). In a bid to achieve this, the NHS recently announced a £4.2 billion investment to drive this initiative with the aim of saving billions, improving services and meeting the challenges of an ageing population (National information board 2014). However, recently there is a pressing realisation that collecting surplus data without the tools and, importantly skills to interpret it correctly, is a hindrance for organisations (Matthias et al. 2016). Consequently, the extant literature is now calling for more studies exploring how people use and manage BI tools (Grabski et al., 2011), and more specifically how managers can derive actionable insights from the data (Sharma et al., 2014). Due to an academic focus on the BI technologies, little is known regarding the use of

these applications by organisational actors; while there is also agreement between academics that little is known regarding the skills necessary for driving value from the substantial amounts of stored data (Miller 2014).

1.3.1 Research aim and objectives

The public sector has huge amount of data and high system complexity (Wang and Liao 2008) and the evaluation of IS considerably differs between private and public organisations (Rosacker and Olsan 2008), Yet, most IS related research has been focused on the private sector (Gaardboe et al. 2017). Thus, given such complexity and the dynamic nature of the NHS, there is a pertinent need to explore how BI is being used and more importantly the consequence of this on key organisational actors, particularly given the strategic direction and recent data-driven push of the NHS. Accordingly, Shollo and Galliers (2016) kindle a new direction for BI research which this research will contribute towards further. Their study utilises Weicks (1995) sense-making framework which explores BI decision making in an illustrative interpretive case study, to gain deep insights into BI users and their interactions with BI systems from a financial industry context. Shollo and Galliers (2016) investigate the role of BI in facilitating organisational knowing, yet there remains a lack of understanding relating to the impact BI systems have on organisational actors, such as the data analysts and decision-making managers and the degree to which their roles influence how BI data is used.

While an emerging stream of healthcare literature has focused on intra-organisational dynamics between actors, this has been largely from a Management-Clinician dyad (Spehar et al. 2014), however given the emphasis on BI in current times, organisational actors such as data analysts are becoming increasingly relevant from intra-organisational contexts. Thus, the viewpoint of active BI organisational actors namely BI analysts and functional managers will be central to this research, as opposed to technical workers, BI developers, system engineers or any other closely related positions. This strand of BI literature is in its infancy, therefore presenting various research

opportunities. Current literature lacks BI research which takes a human-centric approach (Matthias et al. 2016), consequently, researchers stress the need to understand the role of users, by exploring how organisational structures, routines, decision-making processes and technologies impact the ability of decision makers to produce insights from data (Sharma et al. 2014). It is necessary when exploring a potential area of research to set parameters and specify the scope of the intended study, particularly for this research, due to its vast intertwined nature. Consequently, this research focuses on the organisations internal environment with the aim of examining various organisational actors and their interactions with BI systems.

In addition, Pouloudi et al. (2016) call for studies to explore conflicted views and perceptions among individual stakeholders to gain more intra-organisational insights into conflict and power dynamics which may affect public sector IT programs within the public sector. The authors argue the need for such research particularly within the healthcare, given the fluctuating, yet dominant nature of power and influence held by multiple stakeholders. As such, the aim of this research is as follows:

"To explore how intra-organisational power dynamics between actors is impacted as a result of their interactions with Business Intelligence systems. In doing so, formulating a conceptual framework which allows healthcare policy-makers to identify shifts in power between individuals which may have implications for the success of BI projects"

This is of importance, particularly given recent IS related healthcare failures (Justinia 2017) and due to the criticism directed towards the extant literature for over emphasising technology, while overlooking the people (Swan et al., 1999; Galliers and Newell, 2001; Shollo and Kautz, 2010; Grabski et al. 2011; Shollo and Galliers 2016). Therefore, this research seeks to contribute to this understudied area, by focussing on the following research questions:

- How does the use of BI impact the power dynamics between various organisational actors within the decision-making process?

- What is the impact of BI use within the public healthcare organisation?

- How is BI used by organisational actors within the decision-making process?

1.3.2 Objectives of the research

In order to answer the above research questions, the following objectives are defined and then subsequently achieved throughout the thesis:

Objective 1: To propose an appropriate conceptual framework which will help explore how BI is used by various actors and its implications on organisational power dynamics, while also translating the research needs into research propositions.

Objective 2: To utilise a suitable research methodology, which will assist in identifying the role of human behavioural factors and other key factors which influence BI use and impact power dynamics.

Objective 3: To explore the research propositions and revise the conceptual framework where required.

Objective 4: To offer theoretical and practical implications as well as exploring direction for future research resulting from this work.

1.4 Paradigm, design and methodology

According to Myers (2003), the case study methodology is recognised as a popular qualitative method in the field of IS. Accordingly, this research opts for an exploratory case study design, in which 30 semi-structured interviews were

conducted in order to enable participants to elaborate and further expand on their experiences and draw upon more closer accounts of their own use of BI. There were a number of reasons why the exploratory case study design was considered most appropriate for the research at hand. Firstly, a defining feature of case study research is its focus on 'how' and 'why' related questions (Myers, 2009) and therefore, for this reason is suitable for descriptive and exploratory studies (Mouton, 2001). The use of exploratory case studies is well established within IS research (Hill and Scott 2004; Ponelis, 2015; Fink and Disterer 2006), whereby researchers predominantly take an exploratory and applied focus when investigating emerging technologies or attempting to gain insights into aspects relating to technology previously overlooked (Barnes, Buckland, & Brancheau, 1992), as also is the case in this research.

In relation to the methods adopted for this research, interviews, participant observations and document reviews all form methods for data collection, thus the researcher relied on the accounts and experiences of the participants, alongside the subsequent interpretations derived from the analysis of these accounts, thus further advocating the interpretive premise for this study (Orlikowski and Baroudi, 1991).

1.5 Key findings and contributions

This research offers insights into how the use of BI impacts power dynamics between organisational actors within a public sector context, therefore presenting a number of key contributions to both theory and practice. Firstly, by answering the call of Sharma et al. (2014), who highlight a lack of insights into how managers use BI and data analytics for creating actionable insights, the findings from this research contributes new knowledge to BI literature, through offering insights into human factors relating to BI decision-making, an area largely overlooked within BI decision-making literature. Therefore, findings from this research build on the work of Shollo and Galliers (2016), by exploring in more detail the dynamics present during BI articulation.

In addition, this research offers a significant contribution to healthcare literature by providing new insights into the manifestation of influence and power between healthcare actors, which to date has mainly been explored from management and clinician lenses within healthcare literature. However findings of this research uncovers power dynamics between analysts and managers, thus offering another perspective which looks beyond the management-clinician dyad typically associated with this stream of literature. This too answers the call by Pouloudi et al. (2016) who emphasis the need for studies to explore conflicted views and perceptions among individual stakeholders in order to understand internal conflict and power dynamics which may impact public sector IT programs, particularly in the healthcare. Furthermore, the key theoretical contributions of this research are in the form of a conceptual framework namely 'BI Power Enactment Framework' and the 'BI Power Matrix' which were developed as a result of the findings from this research, which can act as a human-centric guide and can be applied as lens for future researchers to explore the impact of BI on intra-organisational dynamics.

The research also bridges theory and practice through its key findings and has practical relevance for practitioners, by detailing how BI impacts power dynamics between organisational actors within a healthcare context. Given recent data-driven trends and increasing BI adoption within public sector organisations, the findings provide practical recommendations which policy makers can consider to effectively manage power dynamics between organisational actors resulting from technological influences such as BI. Furthermore, the 'BI Power Enactment Framework' which can also be applied by practitioners to tease out power dynamics amongst BI users, through firstly exploring how the divergent organisational actors use BI and secondly by identifying factors which impact power dynamics, thus enabling senior management to identify shifts in power dynamics, which may impact the success of IS driven initiatives.

In addition, policy-makers can also utilise the 'BI Power Matrix', which offers a four-way perspective of establishing the influence of an organisational actors, namely through the degree of institutional knowledge they possess, their

analytical skills, the degree to which they are able to attain legitimation from senior management, and the extent to which others in the organisation depend on them due to their skills.

1.6 Structure of thesis

This thesis is structured in accordance to the recommendations forwarded by Phillips and Pugh (2005) and is made up of the following key elements: (1) background theory, (2) focal theory, (3) data theory and (4) novel contribution.

The background theory consists of chapters 1 and 2. Chapter 1 serves the purpose of introducing the initial focus of the research, the research problem and the research question which this thesis will explore. Based on this, chapter 2 further frames and underpins this research by critically analysing the existing literature, whilst allows for the identification of both a conceptual model that can be tested as well as gaps in the existing literature.

Accordingly, this contributes towards the development of the second element of the thesis (focal theory) which concerns creating a conceptual model that is tested as part of the research (chapter 3). The data theory is the third element of this research which in chapter 4, addresses the philosophical underpinnings of this research, explores the development of a suitable research methodology and the challenges associated with this approach. Chapter 5 provides contextual details relating to the case organisation, whilst chapter 6 provides detailed insights into the data emanating from the chosen case study, thus providing the empirical foundations to the thesis. The fourth and final element (novel contribution) addresses the findings of this research and relates it to the wider field, thus presenting the practical and theoretical contributions of this research (chapter 7). Chapter 8 concludes by summarising the research, its contributions and proposes potential direction for further research resulting from this study. Accordingly, the four key elements of this research are incorporated across the eight chapters of this thesis.

2.0 CHAPTER 2: Literature Review: Critical analysis of research area

2.1 Introduction

This chapter provides the background literature that underpins this research, highlighting the gap in knowledge and providing justifications for this research. BI is a field of increasing relevance for both industry and academia. Despite still being observed from its technological origins, it is gradually expanding to cover beyond its traditionally technical focus towards non-technical, managerial elements and human related processes, as intended for this research. Thereby, the focus of this research is on the non-technical managerial perspectives, in particular the impact of BI on the users and their use of power resulting from BI use. Accordingly, the users of BI are central to this research.

The onsets of technical advancements, such as BI have transformed the way organisations conduct business, increasing competitive advantage, overcoming global competition, thus becoming crucial in current times (Gudfinnsonn et al. 2015). Luftman and Ben-Zvi (2010a, 2010b) report BI as being widely recognised and favoured globally, ranked by IT leaders as the 3rd top application and technology development in European companies, 2nd highest for South-East Asia and Latin Americans, whilst consistently being ranked the highest in the US. Unsurprising Luftman and Zadeh (2011) refer to BI as being a highly influential and key technology in organisations. Luftman and Ben-Zvi (2010b) posit the popularity of BI across various geographies indicates how organisations have abundance of data, yet lack insight, hence their pursuit of BI applications and tools to aid and make sense of data. The insights which BI is able to supposedly achieve through analytical tools cannot be achieved from only possessing vast depositories of data, rather BI requires organisational actors to make sense of the data, thereby converting it into actionable and valuable information and possibly knowledge for decision-making purposes. These very insights, achieved through decision-makers interactions with BI systems are central to the research.

Wixom and Watson (2010) identify various research opportunities that can be explored in the field of BI, which includes BI inspired decision making. The authors posit currently fragmented discussions relating to how BI fits into organisational decision making, and what implications this has for organisations. This direction for further academic research is the consequence of BI studies currently overlooking these areas, and instead focusing on the design, development and application of BI tools (Yi-Ming and Liang-Cheng 2007), the cost and benefits of BI (Hocevar and Jaklic 2010), impact of BI on organisational performance (Elbashir et al. 2008; Elbashir et al. 2011; Wieder et al. 2012), competitive advantage (Elbashir et al. 2013; Peters and Wieder 2013), and generally focusing on BI technologies (Shollo and Kautz 2010). Consequently, the traditional focus of existing BI studies, the continued growth and attention surrounding BI and particularly the gap in BI knowledge relating to the impact of BI on its users, and the wider intra-organisational dynamics is a justified basis for the research at hand.

2.2 BI definitions – Overview

BI has divided both practitioner and scholarly opinion, meaning different things to different people. However BI in simpler terms can be described as an approach which allows large volumes of historical information to be analysed by users for decision making and managerial support (Eckerson, 2003). Nonetheless, ever since the emergence of the term BI, many definitions have surfaced. For instance, various authors support a broad, holistic definition of BI, viewing it as a sophisticated approach to decision support (Alter 2004). Similarly, BI is also viewed as an encompassing umbrella term (Eckerson and Howson 2005; Gartner 2015). However, some have understood BI more specifically from a technical perspective, emphasising the technology that facilitates BI (White 2005; Glaser and Stone 2008), BI as a product (Lönnqvist and Pirttimäki 2006) or alternatively from a managerial point of view, focusing on its processes rather than just the technology (Azvine et al., 2005; Negash 2004). Consequently, it is argued that while there is no universally accepted

definition of BI, there is some agreement between scholars on that it can be categorised from process, technology and product contexts (Dooley et al., 2017). Chee et al. (2009) explain these perspectives further by considering the technological element of BI as a BI system, whereas the process aspect can be understood as the implementation of the BI systems. Additionally, they regard the product perspective as being associated with the requirement for actionable information with specific tools.

Amidst the array of positions reported in the literature, multidimensional definitions of BI also exist. Shariat and Hightower (2007) and Baars and Kemper (2008) understand BI as more than just a technology, process or even product, but rather a combination of these. It is a consequence of such divergence, that Štefániková and Masárová (2014) describe the field of BI as being 'terminologically fragmented'. These differing definitions and interpretations contribute in creating a sense of obscurity and vagueness.

Although the multi-dimensional position of BI is an amalgamation of various views, it still associates to either one of the main views, either the process or the technical view. For instance, Wixom and Watson (2010: 14) define BI as *"a broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users to make better decisions."* Whereas, Davenport (2006 106:107) describe BI as encompassing "*a wide array of processes and software to collect, analyze, and disseminate data, all in the interest of better decision-making."* The aforementioned scholars appreciate the role technologies and applications play in supporting the processes of collecting, storing and analysing data. Yet, their definitions acknowledge the technical elements of BI, while placing emphasis on the processes and specifically decision-making, hence aligning these seemingly multi-dimensional definitions of BI closer to processes and decision-making perspectives rather than only its technology.

The definition of BI for the purposes of this study is in line with Wieder and Ossimitz's (2015) understanding of BI. The authors also take a multi-dimensional understanding of BI by synthesising the definitions outlined by Foley and Guillemette (2010) and Wixom and Watson (2010) and thus

understand BI as "*an analytical, technology supported process which gathers and transforms fragmented data of enterprises and markets into information or knowledge about objectives, opportunities and positions of an organisation*" (Wieder and Ossimitz 2015:1164). This encompassing approach to BI is of particular importance for the purposes of this research for several reasons. Firstly, this definition appreciates the supporting role of technology in BI, whilst emphasising the processes and its role in transforming data into information as well as knowledge. Secondly, positioning BI in such a way highlights the entire process of handling data through to its role in supporting organisational decision-making, which is the central focus for this research. However, various other concepts closely aligned to BI have also advanced during this period, that requires framing for the context of this research.

2.2.1 BI and related concepts

The seemingly lack of scholarly agreement of BI and its associations with data, information, knowledge, processes and technologies, highlights the entwined nature of this field. In addition, given the extensively diverse application areas of BI, and the advancements in technology, this section provides a holistic, yet significant overview of the fluidity and rather interconnected nature of other key concepts closely related to BI. For the purposes of this research, BI is understood as an encompassing umbrella term (Wieder and Ossimitz2015; Gartner 2015) and amidst the divergent interpretation of BI, this rounded definition can assist in reducing obscureness and confusion, allowing other concepts to position within the conceptual umbrella of BI. The key concepts that are closely associated with BI or interchangeably used and projected as BI will be discussed in the forthcoming section. These concepts are:

- Knowledge management
- Competitive intelligence
- Business analytics

Each of the aforementioned concepts belongs to an extensive body of literature which will not be entirely covered, as this is not relevant for the purposes of this research. Hence a succinct overview of these concepts is undertaken in order to establish their relationships and positioning to BI.

2.2.2 Knowledge Management (KM)

BI along with KM also has the tendency to be misrepresented, therefore on occasions wrongly applied in organisations to resolve issues that are beyond its remit, scope and purpose. As a result, extensive KM projects lead to failure, primarily due to limited understanding of what KM offers. (Cody et al. 2002; Chung et al. 2003). Furthermore, both BI and KM are often used interchangeably, with a lack of clarity between what each constitutes. This false association has been supposedly reported in industry, whereby a survey conducted by OTR consultancy found 60 percent of consultants were unaware of the differences between both concepts (Herschel and Jones 2005).

Although, the context and scope of the OTR survey are not provided, the literature relating KM and BI also indicates the interchangeable use of both concepts, although they differ in reality (Becerra-Fernandez and Sabherwal 2015). This can be reflected through the central research aims of previous studies that aim to integrate both BI and KM systems together (Cody et al. 2002; Herschel and Jones 2005; Rao and Dey 2012). Although BI and KM are discrete, their distinctions are not apparent due to their involvement in similar activities and processes (i.e., capturing, organising, analysing, applying data). Both concepts, to some extent, promote some degree of decision making, understanding and learning whilst also dealing with intellectual components. The varying interpretations and offerings of BI are explored in detail later, however holistically, distinctions between BI and KM are reported based on the types of knowledge they deal with. BI is attributed to explicit knowledge, whereas KM is seen as encompassing both tacit and explicit knowledge types (Herschel and Jones 2005).

Khan and Quadri (2012) similarly distinguish between both concepts through their dealings with knowledge, also affirming that BI handles only explicit knowledge. This type of knowledge is defined as objective, technical knowledge which can be formalised, coded and deposited. On the other hand, KM deals with tacit knowledge, which can be described as a subjective and cognitive type of knowledge. In addition, Becerra-Fernandez and Sabherwal (2015), propose inputs of BI are data and information, whereas information and knowledge are the inputs of KM.

It is due to this that Herschel and Jones (2005) position BI as a subset of KM. However, KM is also referred to as an 'internal-facing BI' that distributes intelligence amongst the organisational workers allowing them to effectively perform functions within their business domains, and in turn managing knowledge through the use of various BI techniques (McKnight 2002). Therefore, in contrast, this does not align KM and BI in conjunction, but rather organises KM under BI. This position is also upheld for this research since the opposing view (BI as a subset of KM) is established on the premise that KM encompasses both tacit and explicit knowledge types, whereas BI only focuses on the latter, due to this understanding BI is viewed as a component of KM. Shollo and Galliers (2016) however posit that BI also deals with tacit knowledge, therefore defying the underlying basis for Herschel and Jones (2005) to place BI under KM. Additionally BI systems are the most recent in the line of IS technologies, advancing on from KM, both as a buzzword and as a concept.

2.2.3 Competitive Intelligence (CI)

The disparities between BI and KM are subtle, similarly associations between BI and CI are also loosely reported. Several views relating to the associated between BI and CI can be gleaned from the literature. The first perspective draws no distinction between BI and CI, for instance, Vedder et al. (1999), Kinsinger (2007) and Calof and Wright (2008) all offer no dissimilarities between the terms. Calof and Wright (2008) affirm that CI fully compromises all aspects relating to the competitive environment, which incorporates,

existing and potential competitors, by the means of collecting both internal and external information which in turn, allows organisations to recognise opportunities, whilst also detecting threats. Vedder et al. (1999: 109) categorically associates both, intertwiningly, by suggesting, *"CI is also known as business intelligence*". Though, according to Štefániková and Masárová (2014) this position is primarily established in American literature thus highlighting the potential regional influences on the interpretations of these concepts.

The second position regards CI as a component of BI, therefore defining CI "*as a sub discipline of BI"* (Obeidat et al., 2015: 48). Zheng et al. (2011: 698) also support this view by stating that "*CI has emerged as an important area within BI"*. Weiss (2003) and Štefániková and Masárová (2014), also views CI as a product of BI, alongside a plethora of other BI tools. This emphasis of BI as a wide-ranging umbrella concept for CI and other associated intelligence terms (such as, competitor intelligence, market intelligence, customer intelligence, and strategic intelligence) is particularly evident from European literature and is expressed in Figure 2.1, contrary to American literatures synonymic interpretation.

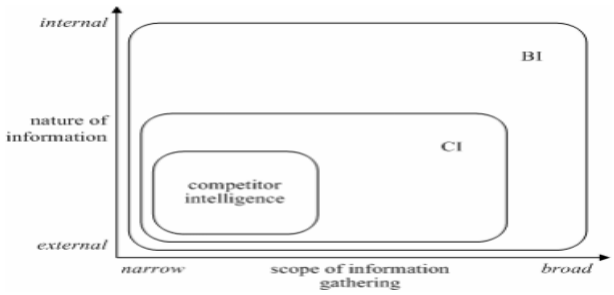

Figure 2.1:Intelligence concept scope and nature (Source: Choo 2002)

The last perspective views both BI and CI as being distinctively separate Information Systems (IS). Špingl (2007) furthers this by suggesting that CI focuses on the external environment, whilst BI principally pays attention to

internal matters, therefore both inherently deal with different information sources. Yet Choo (2002) posits that BI has the ability to deal with the organisations strengths and weaknesses, whilst equally being capable of dealing with an organisations external environment, such as competition, economic and political factors. Zheng et al. (2012) concur, but reveal BI systems are struggling to fully provide the CI proposition due to difficulties in obtaining data of external environments, with many industries relying on third party data providers (such as AC Nielsen) for their CI requirements. While, the BI systems that do offer such capabilities such as offering comprehensive information on competitors are costly and often based on historical data, as opposed to real time data.

In summation Choo (2002) states that BI has the most extensive scope midst all the concepts of intelligence. BI is responsible for monitoring, collecting, processing, analysing data for the entire business environment, not only for customers, markets and competitors, hence highlighting the superiority of BI from all the other intelligence processes within the business segment (Bartes, 2010). Therefore, in order to understand BI and avoid further misinterpretations, for this research BI is understood as the 'parent category' that inhibits and encompasses various technologies and concepts, such as CI.

2.2.4 Business Analytics (BA)

Watson (2015) argues that concepts and names are constantly changing in the field of decision support by vendors, professionals and writers in a bid to attract their relevant stakeholders to their products / concepts. In addition to the ambiguity surrounding the other concepts described earlier, the term 'analytics' has also gained popularity in recent times. Similar to BI, the term BA is increasingly recognised as an umbrella term (Watson 2011). The BA notion took off during the analysis periods (Arnott and Pervan 2008), and its popularisation can be attributed to the studies of Davenport (2006) and Davenport and Harris (2007). The widely accepted definition of BA is also endorsed by Davenport and Harris (2007: 7) who express BA as; "*the extensive use of data, statistical and quantitative analysis, explanatory and*

predictive models, and fact-based management to drive decisions and actions." Although Arnott and Pervan (2014), refer to this definition provided by Davenport and Harris (2007) as being 'similar, if not identical' to BI.

Laursen and Thorlund (2010) understand BA as an advanced branch of knowledge within BI, whilst BA is also viewed as merely a subset of BI (Davenport and Harris 2007). Some authors maintain both terms share synonymic values, others separate them maintaining BI as being a subdivision of analytics (Sircar 2009), while some have presented them as an amalgamating pair denoted as 'BI and A' (Chen et al. 2012; Corte-Real et al. 2014). Arnott and Pervan (2007) maintain that majority of IT practitioners and managers do not see a major difference between both terms.

Casado (2004) express that although defined differently according to their perspectives, all the differing definitions share the same focus, with the central tenants and idea of data analysis and information dissemination (Lonnqvist and Pirttimaki 2006). This is also reflected by Gudfinnsonn et al. (2015), who, use the terms BA and BI interchangeably. In addition to this, Williams (2016) outlines that the emergence of new terms, such as' Big Data (BD) or cognitive business is about the same thing that BI has always been about, therefore further highlighting the fluidity of the terms in this encompassing field of BI.

However, Sharda et al., (2018) makes the distinction between BI and BA by highlighting that BI is typically associated with descriptive analytics, which utilises historic data to assist in the understanding of what is happening within an organisation. Alternatively, business analytics in general refers to more advanced forms of analytics such as predictive analytics, which utilises statistical methods to in order to uncover patterns and capture relationships in data to predict future events (Anagnostopoulos, 2016). Additionally, business analytics also relates to Prescriptive analytics, which utilises both descriptive and predictive analytics to deals with questions which typically explore what should be happening within a particular context and how best to influence it (Tiwari et al., 2018).

Therefore, it can be argued that concepts such as KMS, CI and BA are components which connect and relate to BI, however for the purposes of this research and in line with Laursen and Thorlund (2010) and Sharda et al. (2018), BI will be understood as the descriptive form of analytics. Additionally, the phenomenon of BD can be understood as the latest chapter of BI, considered as the next generation of data warehousing and analytics (Minelli et al. 2013) and described by the large amounts of, new and uncommon forms of data (social media) and superior technologies (Hadoop, predictive analytics) associated with it (Wixom et al., 2014). However, BI is the focus of this study, given its wide application across various industries and continued organisational relevance.

2.3 The Technical view of Business Intelligence

This research focus is on the human element of BI that is often overlooked in the extant literature, particularly the organisational actors and their interactions with BI systems. Hence positioning this research from a process perspective of BI is appropriate. However, the technical perspective cannot be overlooked, as the 'people' relevant in this research are the active users of the BI technology. The people and technology are inseparable, as capturing real value of BI requires organisations to integrate BI into the management process to assist in effective decision-making (Williams 2004). Similarly, Shanks et al. (2010) posit that integration of BI technologies to the organisational decision-making processes is paramount. Thus, in order to achieve this integration, an understanding of what role these technologies play in the decision processes is required otherwise BI utilisation may have limited success (Watson et al., 2002). Furthermore, when engaging with the technical BI literature, discussions relating to various forms of technologies are inevitable, particularly as the initial rise and popularity of BI as a term is attributed to technical advancements (Watson, 2009).

The scholars adhering to the technical perspective pay attention to the architecture, development and emphasise the use of tools and technologies that assist in transforming data into information, and even into knowledge for

design making purposes. The emphasis on the technology is at the forefront, which explain how the technologies enable the *"recording, recovery, manipulation, and analysis of information"* (Petrini and Pozzebon 2009:181). Yet, BI is understood differently from within the technical stream of literature, although its primary focus is on the technology. Some advocates of this perspective also explicitly appreciate the processes that are supported by these technologies (Clark et al., 2007; Negash, 2004) although the focus is not on the actual processes, rather on the array of technologies that facilitates the use of information (Watson and Wixom 2010). These BI technologies closely link them to an array of different resources in the form of applications, sets of systems, packages, tools and platforms (Petrini and Pozzebon 2009). Hence, a plethora of apparently divergent applications is generally referred as BI.

The provenance of BI, in particular the technical view can be traced from within the DSS genealogy, with its eventual replacement of the EIS and DSS terms. Watson (2011) refers to EIS and OLAP as part of the DSS portfolio, however BI emerged in order to progress the improvements achieved through the DW, ETL and OLAP technologies. Watson (2009) expresses that the widespread popularity of BI as a term, impacted the DSS name, which as a result endured change. With the rise of BI, in particular the technical emphasis, the once common and widespread terms of DSS and EIS 'virtually disappeared'. It is therefore understandable, why Arnott and Pervan (2014) believe the DSS and subsequent fields suffered a 'crisis of relevance' by the mid 2000's. BI from this perspective compromises DW technology, OLAP and data mining (DM), whilst it is understood that inputs are received from KMS, DSS, enterprise resource planning (ERP), EIS and from additional forms of IS (Negash 2004).

2.4 The Process view of Business Intelligence

The alternative BI perspective is identified by synonymic terms, such as the practise view, business perspective and managerial approach, however the process view is generally the accepted term for this stream of literature (Petrini and Pozzebon 2009; Olszak and Ziemba 2010; Shollo and Kautz 2010; Shollo and Galliers 2016). Nonetheless, they refer to the same stream of literature

which overcomes the limitations of the technical view (Shollo and Galliers 2016). The process view understands BI as a continuous 'process' for decision-making whereby internal and external data are gathered, analysed and integrated to generate information appropriate for the decision-making 'process' (Petrini and Pozzebon 2009: 178). According to this perspective the role of BI is to create an 'informational environment' that reveals 'strategic' business elements, centrally focusing on the processes, whilst the role of technology is largely recognised for facilitation and support purposes. This stream of literature is pertinent due to its focus on processes, and peripheral emphasis on BI technology. Olszak and Ziemba (2007) depict the BI processes in conjunction with the technologies at each phase in Figure 2.2.

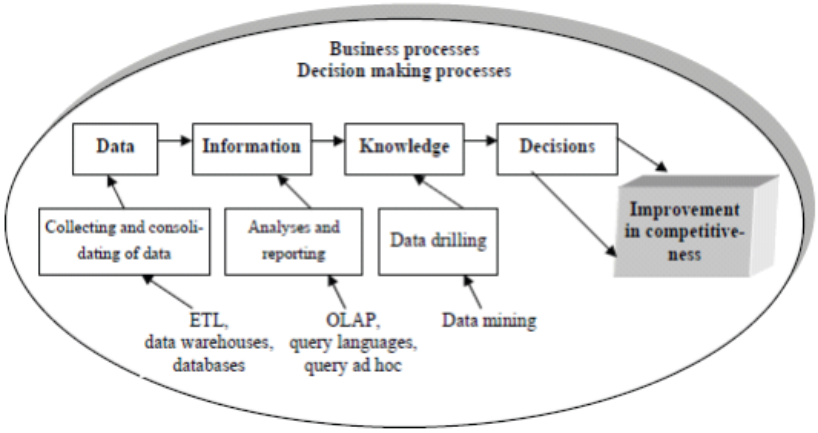

Figure 2.2: BI processes (Source: Olszak and Ziemba 2007: 137)

Lanqvist and Pirttimaki (2006) advocate the process stream of BI, by understanding BI as playing a major role in the control and movement of business information, which is identified and processed into meaningful managerial knowledge and intelligence. Pirttimaki (2007) refers to BI as the approach of processing and enriching necessary information for managerial use. Although the authors of this stream emphasis the processes as opposed to the technology, the interplay between both is evident in the definitions penned within this stream. For instance, Davenport (2006), a key advocate of the BI process view defines BI by placing emphasis and priority to processes,

yet appreciating the supporting role technology plays through necessary tools for analysing, and reporting purposes.

Moreover, it is also imperative to recognise which aspects of BI the process literature acknowledges. While the technical perspective considers various BI phases, the process perspective also recognises the systematic phases of BI, which involves data being analysed, transformed into information, and then further refined for the decision-makers. Thus, the focus of this steam of literature is on the analysis, organisation and presentation of the information.

Thus, Petrini and Pozzebon (2009) highlight the ‘separation’ between the technical and process perspectives, as the latter is seen as looking beyond just the ‘technology’ and focusing on the methods that are used to exploit the data which passes through the various technologies. In addition, the technical literature also seemingly assumes that once the various BI technologies have served their purpose during its chronological phases, that this leads to improved decision-making. However on the contrary, the literature of the process perspective attempts to look more closely at the relationship between BI and decision making processes, rather than merely resorting to assumptions. According to Shollo and Kautz (2010), this perspective places more importance to how information that is derived from BI is actually applied and entrenched in the decision-making process. Although the process view establishes a closer position in identifying the association between BI and the decision-making process, this still lacks attention from the advocates of the BI process perspective. Arnott and Pervan (2008) concluded that a large quantity of BI studies have been dedicated to BI technologies, focusing particularly on its architecture, development and application, as opposed to seeing how BI derived information is utilised in decision-making processes.

Of the scarce studies addressing the decision-making process directly, Davenport (2010) can be credited with the initial attempts to align BI to organisational decision making. Affirming that in order for organisation to achieve favourable performance outcomes from their BI systems, they should focus on their decision processes. He outlines a framework of how

organisations link information and decisions, categorising decisions as loosely-coupled, structured human, and automated. The most common association views information as loosely supporting a variety of different decisions, however this approach fails to establish which decisions are reached via which information.

In addition to this, Davenport (2010) further describes a 'structured decision environment' which is created as a result of the use of specific tools, implementing analysis to support particular decisions, behavioural techniques and methods responsible for improving the accuracy of the information. This decision environment enables the use of specific information for the purposes of improving specific decision processes. The final method indicates information as being identified, codified in such a manner that allows for automated decisions to be made by machines. Therefore, Davenport (2010) must be recognised and commended for attempting to describe how organisational information derived from BI links to the decision-making processes. While Davenport (2010) offers a rare decision-centric perspective from within the BI literature, by attempting to describe how BI links to decisions within organisational settings. However, many questions remain unanswered as to how BI output is used by decision-makers, and what impact this has on the interactions and power dynamics between various users of BI.

Differing opinions that manifests even from within the same stream of BI literature are also evident when discussing the output of BI processes. Though there is agreement amongst the scholars that BI is recognised as a continuous process, some scholars, notably those who refer to BI as CI see the output of BI process as relevant information which has been transformed from the gathered data, whereas others take it further and understand knowledge as opposed to information as the generated output of BI processes. The viewpoint that knowledge is the output of BI, stems from the understanding that data and information is transformed in order to support decisions and drive actions. This notion places emphasis on individuals' knowledge as a prerequisite for the effective use information (Jensen and Meckling 1992; Choudhury and Sampler 1997). However, subsequent studies that acknowledge knowledge related

insights from within the process view have also played their part in mystifying further how BI output is applied in real organisational settings.

2.5 Bridging the perspectives of the Technical and Process views

Despite the obvious divergent paths both streams of BI literature take, they also share common ideas, much of which can be attributed to the intertwined interplay between the 'process phases and the technologies' that facilitates them. Firstly, the review of extant literature from both perspectives highlights the central focus of BI of gathering, storage, analysing, and distribution of information (Petrini and Pozzebon 2009). Whilst concurring with this position, it would be correct to take this further and state that the core of both BI perspectives concerns the gathering, storage, analysing, and utilisation of either (or all) data, information and knowledge. Secondly, the underlying goal of the technical and process BI is to aid organisations in their strategic decision-making processes. Thirdly, the 'assumption' that BI leads to better decisions, be it through the use of information or knowledge, is also propagated by both perspectives in some capacity.

Subsequent studies have attempted to address the casual link between the availability of more information and better decision making (as discussed later). However, the extant literature of both perspectives bridges its differences on these ideas that rationally assume more information leads to less uncertainty, thus improving the decision-making process and thereby leading to more superior decisions. Thus, studies of the technical stream that focus on the architectures and implementation of BI technologies, attempts to describe the relevant processes from a rational disposition. Similarly, the process advocates that study the unfolding of BI processes in organisations attempt to describe them from a similar rational and linear manner.

It can be argued that such orientations from an organisational context are unrealistic. For instance, this seemingly rational outlook to decision-making assumes that BI decision-making is a seamless transformational process, which transforms data to information, through to actionable knowledge, which

in turn leads better decisions (Golfarelli et al. 2004). However, the information required for decision making is not always comprehensible, and often is ambiguous, unclear and not necessarily free from uncertainty. Hence, the rational lenses to oversee BI decision-making from both the perspectives can be questioned and challenged. Additionally, there is no agreed consensus within each of the two perspectives pertaining to what the outputs of BI are.

Furthermore, a core focus on design and development of BI technologies is clear from within the technical stream. Much of this can be attributed to BI not reaching maturity as a research field, but rather still developing, and mainly focusing on technology and getting data right (Arnott and Pervan 2008). Additionally, it was not till 2005 onwards, that management support practice saw the emergence of BI as a research field from within the field of DSS (Arnott and Pervan 2014), though BI technology was at its forefront. Additionally, descriptive studies relating to the implementation of BI systems can be seen as succeeding the earlier emphasis of BI technologies in the technical view, though no weighty or relevant insights were directed during BI studies from a decision-centric, decision making perspective. Similarly, from the process literature, a plethora of studies emphasised the gathering and analysing of data and information from the organisational managerial context, yet failing to report how the information (or knowledge) is used by decision-makers in decision-making. Therefore, it is generally agreed by both streams of literature that better decisions are reached through the use BI.

Davenport (2010) opens the doors to potentially a new and relevant stream of decision-centric BI literature. He attempts to describe organisational decision-making processes through its links to data and information, the understanding of the use of its output in the decision making processes, however, how the BI output is used by decision-makers to reach decisions, and what impact this interaction has on its users and the organisational dynamics remains undebated in the extant literature. The review of BI literature also highlighted more progress in the knowledge of the technical stream as compared to the knowledge of process literature. While the technological functionalities and features of the BI technologies and tools have been subject to vast academic

interest, the same cannot be attributed for the BI methods (process view) that are facilitated by these technical tools (Petrini and Pozzebon 2009), or solely BI decision makers perspectives.

Overall, BI scholars have differing views pertaining to BI processes and outputs. The technical adherents hold conflicting views on what the BI technologies are doing, whilst the process view supporters differ on what they understand of BI processes, be it data, information or knowledge. These concepts of data, information, knowledge have historical undertones and been the subject of discussion for decades by system theorists (Zins 2007), it also has relevance from within the contemporary BI context. Table 2.1 displays various positions related to data, information and knowledge:

Author(s)	**Data**	**Information**	**Knowledge**
Wiig 1993	-	Facts organised to describe a situational condition	Truths, beliefs, perspectives, judgements, know-how and methodologies
Nonaka & Takeuchi 1995	-	The flow of meaningful messages	Commitments and believes created from these meanings
Spek & Spijkervet 1997	Not yet interpreted symbols	Data with the meaning	The ability to assign meaning
Davenport 1997	Simple observations	Data with relevance and purpose	Valuable information from the human mind

Davenport & Prusak 1998	Set of discrete facts	A message meant to change the receivers perception	Experience, values, insights and contextual information
Quigley & Debons 1999	Text that was not answered questions to a particular problem	Text that answers the questions; who, when, what, or where	Text that answers the question why or how
Choo, Detlor & Turnbull 2000	Fact / messages	Data invested with meaning	Justified, true beliefs

Table 2.1: Concept overview: Data; Information and Knowledge

Davenport and Prusak (1998) posit that knowledge is neither data nor information yet it is related to both, whilst Ackoff (1989) has outlined that it is through the application of data and information that knowledge is formed, and only through wisdom does this provide value, thus highlighting the interrelating traits of the concept. Knowledge, though closely related to data and information, has been distinguished by many researchers and practitioners of knowledge management (Bhatt 2001; Coakes 2006; Prusak 1997; Wiig 1997; Nonaka and Takeuchi 1995). Therefore, knowledge from an BI and organisation knowing perspective will be revisited in the forthcoming sections.

2.5.1 Emergent Business Intelligence perspective

Recent definitions of BI incline towards a multi-dimensional understanding, which is endorsed by Holsapple et al. (2014) who understand BI, along with analytics as an overall data driven paradigm compromising evidence based and problem-solving characteristics. The authors appreciate the division of the

steams of technology and practice-based viewed, however currently see them combined with business analytics techniques. Following this track, Chen et al. (2012) also emphasises the data-centric characteristic of BI.

From this combined BI perspective, the BI systems are understood to facilitate a continuous process which sees the gathering, storage and transformation of data into information, which in turn is transformed into knowledge for decision-making support. (Lonnqvist and Pirttimaki 2006; Clark et al. 2007). Although the preceding sections have highlighted the assumptions pertaining to various forms of BI output, the knowledge output of BI from within an organisational context has only recently been discussed in greater detail (Shollo and Galliers 2016). Negash (2004) views BI as a form of knowledge, in which the role of BI systems is to transform data into useful information, and then into knowledge through human analysis. Other scholars, as highlighted earlier also view BI systems as an instrument of knowledge creation for decision-making.

Similarly, the current accepted multi-dimensional perspective understands knowledge acquisition as being naturally acquired through the transformation of data into information and then knowledge (Newell et al. 2002). In line with this and as highlighted in the previous section, the narrative that is evident from the BI literature suggests that actionable knowledge derived from BI systems will in turn lead to better decisions. This however requires further examination, as studies have also reported that BI systems do not always fully support decision-makers (Brydon and Gemino 2008) nor is it conclusive that more information leads to better decisions (Shollo and Galliers 2016). This research focuses on the use of BI by exploring this further.

Firstly, by revisiting the earlier technical literature it is evident that the authors acknowledge the creation of knowledge as a result of BI. Jermol et al. (2003) affirm knowledge is collected and stored by these BI related technologies, comparable sentiments are held by Steiger (2010), similarly Clark et al. (2007) appreciate the knowledge acquisition of BI, however the authors hold this position by viewing the knowledge creation as a mental process, whereby knowledge is viewed as a commodity, that can be captured, stored and

transferred (Maier et al. 2001; Nonaka 1994; Gherardi 2000). However, the highly populated technical perspective has been criticised for its excessive focus on the technology, as evident from the technical literature at the expense of the employees, their processes of sense-making (Weick et al. 2005) and knowing in organisations (Davinson et al. 2012).

Due to the literature being heavily orientated to the technical view, the extant BI literature has not fully engaged with insights into how decision-makers make sense of BI from a knowledge creation perspective. BI and its dealings with data, information and knowledge lack accord in BI literature. Data is free from context and managed by systems, though the process of transforming the data into information is often automated, it still however requires the use of personal knowledge, in order for it to be informative within a given context, for specific purposes (Galliers and Newell 2003). Therefore, the very data that is initially context free and raw can begin to reveal various meanings, to various sets of people, once personal knowledge is applied.

Exploring BI from a knowledge perspective requires focus on practises and actions rather than the technology. Cook and Brown (1999) extensively discuss various distinct forms of knowledge and refer to it as not only being of one kind. Therefore, it can be assumed that BI systems also aid 'mental skills' as knowledge creation and learning is largely achieved through participation (Cook and Brown 1999). The knowing perspective therefore views BI system as an active player in knowledge work, thus focuses on 'how' actions are supported by these BI systems, as opposed to viewing BI systems just as 'passive container', (Shollo and Galliers 2016: 344), that allows knowledge to be stored, transferred and analysed as reiterated largely in the technical literature.

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2.5.2 Business Intelligence and Knowledge creation

Knowledge in organisations is a vast and divergent body of literature, consisting of how explicit knowledge developed by individuals within the

context of an organisation is linked to the ‘learning’ at the organisations level (March and Olsen 1976; Sim and Gioia 1986; Simon 1991), how the collective learning of explicit routines can be part of organisational memory (Cohen and Bacdayan 1994), as well as whether an individual’s tacit skills can or cannot be exploited for the benefit of organisations (Nonaka 1994; Nonaka and Takeuchi 1995; Spender 1996). Nonetheless, McPhee and Poole (2001) describe formal knowledge distribution that occurs in organisations, through its formal structures. This form of knowledge sharing is achieved through the exchange of handbooks, and other formal means (Nonaka 1994), whereas on the contrary, Festinger (1950) outlines informal knowledge sharing and communication, which is emergent, unplanned, and voluntary, hence do not abide by organisational formal structures. From the context of organisational knowing, several notable works are evident, which include the works of Choo (1998: 2002). Choo (2002) believes sense making, knowledge creation and decision-making make up the cycle of organisational knowing, which facilitates the flow of information in organisations.

Choo (2002) explores this further by outlining that these very experiences are grounded on shared meanings that surface from the sense making processes. Therefore, the organisational actors play an integral role in the creation of new knowledge, through their sharing, linking and fusion of existing knowledge, both tacit and explicit, achieved through their collective actions and contesting. According to Choo (2002) this process, not only generates new capabilities, but also enhances existing capabilities, therefore facilitating the likelihood of new alternatives and outcomes and possibly increasing the variety of available organisational responses. The organisation knowing Choo (2002) describes is in agreement with previous works in this field. Polyani (1958, 1966), Kolb (1984) and Tsoukas (2009) agree that knowledge created in organisations firstly stems from individual’s direct, or concrete experiences as well as their actions (Kolb and Kolb 2005). These experiences and actions act as a means for monitoring and reflections that lead to the creation of new distinctions. The newly formed distinctions are incorporated and extracted into abstract concepts from which new inferences for actions can be derived through

negotiation. These inferences can be tested and thus aid as guides in creating new organisational learning (Kolb and Kolb 2005).

The role of BI in contributing to organisational knowing is not treading an entirely new path as previous BI literature has shown ‘camouflaged’ support for various strands of organisational knowing. For instance, Watson and Wixom (2010) examine the increasingly vital role of BI in organisations, from merely a peripheral tool for decision support, to growth into a prerequisite for market competitiveness and overall organisational success. The authors highlight BI’s development from single applications, to suites of applications, through to entire BI infrastructure, therefore refers to it as transformative having major influences within organisational settings.

Consequently, Wixom and Watson (2010) refer to the organisations as ‘BI-based organisations’ as opposed to just ‘organisations’, which can be translated as ‘knowing’ organisations, whereby the BI systems drive out and facilitates the organisational knowledge. Although this notion of knowing can be dismissed as being too loosely connected, it does highlight the critically focal role and influence of BI in organisations, beyond a marginal, peripheral scope, focusing not only on the analysis of historical data, but also engaging actively with real-time data analyses for this generation of knowledge (Glancy and Yadav 2011).

More pertinently, the study of Steiger (2010) also shows the earlier traces of knowing from the BI literature. The study based on Nonaka’s (1991, 1994) knowledge spiral forwards a prescriptive BI theory as knowledge creation indicating how BI can focus on the organisational actors, notably the decision-makers in order to uncover and enrich their mental model, whilst improving the quality of decisions. These can be seen as the first indications of knowing incorporated in BI literature, though both studies fail to distinguish explicitly between decision support and knowledge. Regarding decision support, studies indicate that organisational decision making is facilitated as a direct result of BI systems through the detection of opportunities and complications (Truxillo et al. 2012), uncovering customer behavioural trends (Chau and Xu

2012), and business processes (Elbashir and Willems 2007). Thus, Choo (1998) outlines the process of obtaining insights and then using them to facilitate actions links to the organisational knowing processes. Resonating with this, the MIS Quarterly features several studies from the technical stream of literature that attributes BI technology to the extraction of intelligence, or new insights through the use of BI techniques and methods (Hu et al. 2012; Lau et al. 2012; Park et al. 2012), similar to the processes expressed by Choo (1998).

The most relevant study addressing organisational knowing and BI is the case study of Shollo and Galliers (2016). This work is regarded pertinent to this research due to several reasons. Firstly, Shollo and Galliers (2016) are the first to explicitly pay attention to the untenanted discussions regarding the role BI systems play in creating organisational knowledge. Furthermore, their study explores the process in which BI decision-making occurs, as opposed to overlooking, or assuming this phases as evident from previous discussions. In addition, the existing literature fails to address the stages that occur following the BI output. Shollo and Galliers (2016) however focus more closely at the latter stages of BI beyond the BI outputs, in order to explore how knowledge is created and used by the decision-makers.

Therefore, Shollo and Galliers (2016) kindle a new direction for BI research by identifying two key practises of ‘articulation and data selection’ that are activated through BI systems by users in the cycle of organisational knowing. More significantly, the study found that knowledge is created during the data selection phases, where various elements are identified and highlighted to the forefront. Yet, these elements only transform into meanings during the articulation stages. Therefore, the organisational actors’ role in forming the meanings is central during this entire process. Thus, it is argued that the information that is imparted following BI processes is a direct outcome of the ability of the users, who are yet to be examined more closely in this research. Tsoukas (2009) outlines innovation and learning occurs through new distinctions. Once these distinctions are created and recognised, new organisational knowledge becomes visible, therefore when the new

distinctions are acted upon and developed into newer processes or products, or incorporated to new actions the organisation benefits from innovative and organisational learning. However, in order for these new distinctions to be transformed into organisational knowledge, they need to be communicated from individuals, where they reside in the minds as individualised knowledge, to the organisational community through discussions, engaging in much dialogue and contestations, and only when they are accepted by the community can these new distinctions be regarded as organisational knowledge. It is these individualised elements from within the bigger BI picture that has been overlooked in the literature. This research therefore intends to observe the roles of various organisational actors who interact with BI systems, whilst attempting to explore the role of human factors during BI decision-making.

This practical insight of organisational knowing from within the BI perspective provides a new horizon for BI literature that does not only assume the role of information (or knowledge) in decision-making, but directly acknowledges, and explains the processes triggered by BI systems. During earlier discussions, it was highlighted that BI does not manage tacit knowledge, but rather is accustomed to dealing with only explicit knowledge (Becerra-Fernandez and Sabherwal 2015). However, Shollo and Galliers (2016) report that BI systems through articulation and backing of data can also balance subjectivity and objectivity and accommodate the transfer of tacit knowledge between organisational actors. This is in line with the perspective forwarded by McKenzie and Winkelen (2004), who outline that benefits of technology have been traditionally linked to the transfer of explicit knowledge but advancements in technology are now allowing for more sharing of tacit knowledge. The extent to which BI is able to balance subjectivity and objectivity and also assist in the sharing of knowledge will be further explored.

2.6 Business Intelligence triggered practises

The practises of ‘articulation’ outlined by Shollo and Galliers (2016) compromises three key stages; articulating new distinctions; articulating different perspectives and articulating organisational actions. The articulation of new distinctions emerges from the analysts interpretations of the data supplemented with their personal knowledge, however necessitates additional investigation. The differing perspectives are subsequently articulated, contested and negotiated between relevant actors, in order to make sense of the new distinctions. Accordingly, BI users view the BI systems as a tool to foster dialogue with decision makers. The articulation of organisational actions is supported through the ability of BI systems to benchmark and crystallise common patterns from the data.

Organisational attention has to be on the issues picked up during BI analyses. Shollo and Galliers (2016) argue that organisational attention is central to effectiveness of BI use in the context of Organisational knowing. However, the nature of events that may occur during these BI analyses requires further insight. Shollo and Galliers (2016) argue that the ability of BI systems to provide detailed analysis, including longitudinal data, transparent to all, gives it pervasive power and legitimation during negotiations, however to what extent this occurs is still unknown. The authors state that BI data is an *“active agent for a collective process of discussing and negotiating articulated beliefs and practises”* (Shollo and Galliers: 359). Therefore, this research will also explore the behaviours of BI users during these stages of BI decision-making.

2.7 Organisational power dynamics

Factors of Institutional Isomorphism and competitive pressures can often influence organisations to adopt certain forms of technology, including BI. As a consequence, decisions undertaken in the organisation are expected to be framed and justified differently based on the underlying motivation of the initial adoption of the technology (Ramankrishnan et al. 2012). In ‘determinate situations’, whereby the circumstances are routine and mundane, actions are fairly straight forward (Kuhn and Jackson 2008), however it is the potentially ‘indeterminate situations’ that may arise during contestations between

analysts and decision makers that requires closer attention. Kuhn and Jackson (2008) argue that the amount of information transmitted, and manner of its transmission is irrelevant, if there is no consensus and commonality between the actors. Studies have previously criticised knowledge works on their assumptions relating to intercommunal consensuses, that overlook the dynamics of power in organisations (Contu and Willmott, 2003, 2006; Fox, 2000; Handley, Sturdy, Fincham, and Clark, 2006; Østerlund and Carlile, 2005).

The notion of power bases is evident from various fields of the social sciences, including the field of management, where it is commonly associated with the relationships between organisational actors within work settings (e.g. Presthus 1960). However, the concept of power is described as being messy and difficult to define (Walsham 2003), as highlighted by the multitude of opinions on what constitutes power (Jasperson et al., 2002). Although power is considered as a fundamental aspect of organisations, it too is highlighted that power dynamics are under-theorised (Blackler, 2011; Contu and Willmott, 2003; Jasperson et al., 2002; Marabelli and Galliers, 2017). Thus, while Shollo and Galliers (2016) have offered insights into the stages of articulation, which lead to decisions being executed, how these decisions may be influenced by power considerations during such interactions is overlooked. This is of importance, particularly given that issues of social power and organisational politics in context of IT implementation and application have been understood as being prevalent by IS researchers (Pettigrew 1973; Markus 1983).

Accordingly, it is argued that during the ‘contestation and negotiation’ phase (Shollo and Galliers 2016) a variety of factors, including power dimensions may influence the way in which the BI data is used. As a result, studying the role of power in technology innovation may help uncover the dynamics of BI related contestations. Furthermore, studies have highlighted that knowledge is co-created during the processes of communication (Orr 1996). Hence, in order to tease out the power issues resulting from BI use requires an exploration of the communication which takes place between various organisational actors, from varying perspectives. One such approach which

may be suitable in exploring this is through resource, process and meaning sources of organisational power (Hardy 1996).

Strategy-as-practice literature directs criticism towards the way in which power is conceptualised, as something largely exerted by senior management (Kornberger & Clegg, 2011). Despite managerial seniority, organisational actors may have the ability to draw on sparse resources such as political access, information and/or expertise to diminish the influence of managerial actors who are more highly ranked. Hardy (1996), drawing on the work of Luke (1974) refers to this as an organisational resource power. Accordingly, this source of power can be referred to as the influence an actor may have due to the control of resources which groups in the organisation rely on, which in this context may refer to specialist skills, such as BI and the ability to use it. Furthermore, the process source of power refers to dominant individuals or groups who have some degree of control on decision making processes, rules and procedures. It is also understood as non-decision making, as it enables the influential decision makers behind the scenes to regulate the outcomes of decisions through using political routes and procedures, thus preventing others to participate within this process. This highlights the complex and dynamic influences that may not be immediately visible in organisations. The third dimension is 'meaning power', referring to the control of shared meaning between a group of actors by another group of actors, for instance, how organisational actors may have the ability to influence others through the power of meaning, such as influence of managers over analysts, or vice versa (Hardy 1996). In line with this multimodal approach, IS researchers have by tradition, emphasised the significance of the exercise of hierarchical power (i.e. process power) along with the control over resources (resource power) for implementing IT-based organisational change (Jasperson et al., 2002).

Undeniably, one of the most popular and widely utilised conceptualisations of power is the notable work of French and Raven (1959), whose power typology is extensively used by researchers to explore the nature of power within organisations, thus highlighting the relevance of this work within the field of social power. The authors argue that power in manifested in several forms

within an organisation and most notably through formal channels, referred to as legitimate power. Here, organisational actors have a formal position within the organisation, thus by assigning certain power to individuals enables them to effectively conduct their job. Additionally, the authors also refer to reward power through which organisational actors may reward others for desirable behaviour, thus still links to legitimate power given that most commonly it is the functional manager who has position and authority to offer compensation in such a manner. In contrast, the authors also recognised coercive power, which is the ability of organisational actors, such as functional managers to sanction other for non-compliance. While these are forms of power differ, they are essentially type of influences functional managers are able to exercise. Moreover, the ability to influence others within the organisation through the possessing knowledge, which is valuable to other organisational actors or the organisation is referred to as expert power (French and Raven 1959), this may differ to the previous forms of power in that it is personal to an organisational actor, who may not be in an position of authority, yet through the ability to solve problems or perform certain critical responsibilities, can be highly influential. Referent power refers to the power attained through an organisational actor's admiration, loyalty and attractiveness to the extent that the actors is able to influence other as a result of the strong interpersonal skills. The ability to utilise information to influence others was later added and referred to as Informational Power, the sixth base of power (Raven 1993).

Accordingly, it can be argued that the advancement of recent technologies, may have altered how these power bases are exercised by organisational actors, particularly Informational Power, which can be viewed from two perspectives. Firstly, given the pervasive use of IS within organisations, it is evident that the Informational Power may no longer be considered as a means to influence others, given the widespread nature of IS and the subsequent ease at which information and common knowledge can be shared through the organisation, thus diminishing the extent to which utilising information can influence others. However, on the contrary, it is also argued that in order to successfully utilise BI, expertise and informational power are both required. Firstly, having the ability to manipulate and integrate the data, which has

largely been a challenge for organisations (Zheng et al., 2006), and secondly the ability of providing actionable information from such systems is always guaranteed. Therefore, it may be argued that the extent to which BI may impact power dynamics through Expertise and Informational power bases, both being personal power bases requires closely examination. However, it is argued that French and Raven's (1959) paper shows it to be less rigorous than expected given its wide use, whilst also being inappropriately applied to organisational studies of power (see Blois and Hopkinson 2013).

2.7.1 IS and Power

While it is acknowledged that widespread studies have explored the role of power and power dynamics in organisations from varying perspectives, such as power dynamics within customer-supplier relationships (Johnsen and Lacoste 2016), attention has been directed towards the role of IS in exercising power and control across various organsational contexts (Attewell, 1987; Zuboff, 1988; Gray, 2001). Although work has been conducted within the field, such as the pertinent work of Markus (1983), who explore the role of power and politics within the implementation of a management information system (MIS), the use of boundary objects, communication and collaboration (Sapsed and Salter, 2004), knowledge sharing (Simeonova, 2017), the impact of technology on organisational power relations (Allen et al., 2013; Jasperson et al., 2002) and workarounds (Malaurent and Avison, 2016), little attention has been paid otherwise. Thus, the IS-Power dyad requires further attention, particularly given the exponential growth in technology and its continued adoption within organisations, with technologies such as BI and given the fact that studies have called for further insights into the role IS may play on power dynamics within organisations (Koch et al. 2013).

The concept of power has been interpreted differently by different authors, with no consensus on what it constitutes or how it should be applied, as also reflected in Table 2.2.

Power Dimension	Focus	References
Power-Knowledge dyad	Knowledge Management	Gordon and Grant 2005; Heizmann et al. 2015; Hislop 2013; Kaerreman, 2010; Olsson, 2007; Rechberg and Syed 2013; Simeonova, 2017
Foucauldian Power	Relational power, made up of network of relations, constantly in tension, in activity	Foucault 1977
Radical perspective, power	Power is found in social relationships and it is embedded in a structure of rules	Bradshaw-Camball and Murray, 1991
Resistant power	Having the ability to resist power, while conversely implying one's own power	Doolin 2004
Power as Influence	IS implementation, whereby power is measured by the extent to which users had influence during systems development or use	Barki and Hartwick, 1994; Beath, 1991; Dennis et al. 1998
Episodic power over' perspective,	power considered as a restraining force and is linked, i.e 'to control, coercion, forcefully influencing others and authority	Clegg et al., 2006; Kärreman, 2010; Lawrence et al., 2012).
Systemic perspective power	Referred to as a productive force with systemic 'power to' being embedded in social relations	Clegg et al., 2006; Kärreman, 2010; Lawrence et al., 2012

Interpretive Power	Ability to control access to and direct the construction of organizational realities	Bradshaw-Camball and Murray 1991
Processual power	Social relationship; resource dependency; power as Power force	Sillince and Mouakket 1997
Institutional Power	Power based on the relationships in which organizations are embedded	Fincham 1992
Socially shaped Power	Power is derived from the social construction of meaning	Sillince and Mouakket 1997
Structurally constrained power	Structural power focused at the super-organizational level. Power is the structural influence on behavior within organizations including class perceptions and ideologies	Sillince and Mouakket 1997

Table 2.2: Power multiplicity

Furthermore, traditional conceptions of power views power as a capacity which can be in one's possession, and is exercised over other individuals. As such, power is tainted with the view of being something which repudiates, represses or coerces (Lukes, 1974; Clegg, 1989; Bloomfield & Coombs, 1992). Such power notions infer that the shift of organisational power is a consequence of changes in the distribution of organisational resources, for instance, information, which transfers organisational power and influence onto those who possess the resource (Schultze and Stabell 2004) Such interpretations of power are evident from previous IS research (Pettigrew, 1972; Bariff & Galbraith, 1978; Markus, 1981), as well as more recent studies (Pfeffer, 1994; Gray, 2001; Jasperson *et al*., 2002). However, it must be noted that

this ‘Power-over’ position is largely critiqued in that, it fails to acknowledge the relational aspect of power, which are largely expressed by Foucault (1972, 1977, 1978, 1980). He believed that in modern times, the essence of what constitutes societal power has transformed from being the privilege of an individual, to its being made up of *‘a network of relations, constantly in tension, in activity’* (Foucault 1977: 26-27). Thus, power is seen here as essentially being co-produced during social exchanges, as a result of the way in which individuals negotiate meaning relating to existing power relations.

Therefore, influenced by the seminal work of Foucault, IS researchers provides an alternative view on power, used to outline the role of IS in enabling control through computer-based surveillance and monitoring (Ball & Wilson 2000; Bloomfield & Coombs 1992; Orlikowski 1991). For instance, Zuboff (1988) acknowledges the IT-Control dyad, through highlighting the possibility of newer forms of surveillance because of IS. Thus, IS scholars have expressed that technological advancements can impact power through the ability of some actors closely monitoring others, thus bringing about electronic ‘panopticon’. This supervisory gaze, has been considered highly impactful, given that the notion of power exists continually, even in the absence of observer, thus ultimately having the ability to impact and influence the behaviour of organisational actors (Clegg, 1989). Therefore, it is argued that traditionally, IS researchers have viewed the role of IS in impacting power dynamics between organisational actors, through the ability of the technology to evaluate and calibrate the extent to which individuals may perform below a standard considered the norm (Johnson, 1993; Miller, 1994). Thus, the supervision, routinization, rationalization, formalization and mechanization resulting from technology can be considered as tool to control organisational actors and manipulate behaviours.

While it is acknowledged that widespread studies have explored the role of power and power dynamics in organisations from varying perspectives, such as power dynamics within customer-supplier relationships (Johnsen and Lacoste 2016), conflictual IT implementation in a challenging public sector context (Azad and Faraj 2011), IS implementations (Barki and Hartwick, 1994),

Group support system use (Dennis et al. 1998) as well as the role of IS in exercising power and control across various organsational contexts (Attewell, 1987; Zuboff, 1988; Gray, 2001). However, in general, the IS and power dynamics dyad requires further attention, particularly given the exponential growth in technology and its continued adoption within organisations. Accordingly, it can be argued that the advancement of recent technologies, may have altered how these power bases are exercised by organisational actors. In appreciation that the concept of power holds multiple meanings and in line with Japerson et al. (2002:399), this research understands power to include authority, centralization, decision rights, participation in decision making, influence, politics, or power.

2.7.2 Organisational Decision-making

The review of the BI literature, barring Shollo and Galliers (2016) provides limited insights into the decision-making processes associated with BI. While there is an appreciation of the stages of BI, from the gathering of data through to its output in both process and technical literature, these studies take a rational disposition in its understanding of how BI is used for decision-making purposes, which is underpinned by the assumption that better decisions are made as a result of this BI use. Accordingly, in order to appreciate the complexities associated with organisational decision-making, which is largely overlooked in the extant BI literature, this section places emphasis on organisational decision-making and provides insights into how decision-making may differ across various contexts and as a result of various factors.

Decision-making has been explored for many decades, through varying lenses, however it requires closer attention today, particularly given the technological advancements in recent times. Historically, Von Neumann & Morgenstern (1944) strived to demystify the fundamentals of decision-making processes through their rational action theory, which assumed that an individual has preferences amongst a number of choice alternatives, which enables them to rationally choose which option is most appropriate and in their best interests. Coleman (1986) argues that the rational approach gained

prominence within the field of sociology in the 1990's, as a result of the increasing gap between social theory and quantitative empirical research. Accordingly, the choice behaviour of rational decision-makers can be directly applied in regression-based models, thus the rational approach can be seen as providing a theory of action which can imbed empirical research in meaningful descriptions of individuals' behaviour (Hedström & Swedberg 1996). However, this theory is underpinned by a number of assumptions in that decision-makers are expected to be fully acquainted with knowledge pertaining to their environment, that they also have a balanced set of preferences for assessing alternatives and are highly proficient in computation (Samuelson 1947; Von Neumann & Morgenstern 2007; Becker 1993).

However, a notable limitation of this rational decision-making disposition is that individuals do not always take a rational pathway for decision-making. Accordingly, this rational approach to decision-making has attracted much opposition, for instance, it was outlined that organisational actors may not perpetually be self-interested, (England 1989; Margolis 1982), that preferences are not fixed characteristics of individuals (Lindenberg and Frey 1993; Munch 1992), and that organisational actors do not behave in a calculated and idealistic manner at all times (Somers 1989; Vaughan 1998). More recent critiques of the rational model are centred on its underlying notion of the individual as the principal component of decision-making, which represents a fundamentally asocial representation of behaviour (Bruch and Feinberg 2017). As such, many organisational theorists have provided other lenses to view decision-making, which move away from such rational ideals, by emphasising the importance of social interactions and inter-relationships between organisational actors in influencing behaviour (Pescosolido 1992; Emirbayer 1997).

From a sociological perspective, a plethora of empirical studies have investigated the role of social contexts in shaping people's behaviours across various fields (Carrillo et al. 2016; Perna and Titus 2005; Small 2009; Pachucki et al. 2011; Rosenquist et al. 2010). Such attention, moving away from a rational context towards social environments and interactions as unquestionably led to less emphasis on individual-level processes relating to

decision-making. Consequently, decision-making studies have moved towards how individuals make decisions. Therefore, generally, it is widely accepted that the rational choice theory for decision making is insufficient and a poor illustration of the decision-making process. The underlying critique of scholars has been that this rational paradigm in reality makes unrealistic and impractical demands on organisational actors information processing abilities (Bettman 1979; Miller 1956; Payne 1976). While this has been recognised from within decision-making literature, more so by various decision theorists, it is argued that the rational outlook to decision-making is still largely assumed, though more indirectly when observing the extant BI literature.

A large segment of both the technical and process views have been largely focused upon prescriptive and explanatory studies on how organisations gather and analysis data and information. It is argued that literature based on the technical view of BI in its essence would not pay attention to the users, as naturally the focus is on the technology that facilitates the decisions. Whereas, the process literature attempts to look beyond the technology, focusing on methods and elements related to decision making. The BI studies also reveal that the role of BI output in the decision making process is currently looked at from a largely rational view. There is the assumption that data is generated via BI tools, then transformed into information (or knowledge) and ultimately leading to a 'natural' transition of effective decision making, there remain a lack of studies that explore the influence of decision-maker intuition and appropriation that occurs and contributes to decisions during the process of decision-making. The notion of rationality in decision-making has been challenged in previous works, as the ideas of personal judgment; intuition and intervention are not appreciated in a rational approach (Langley et al. 1995; Bazerman and Moore 2008). The research will build on this perspective from the point of view of organisational actors.

One of the earlier opponents of rational decision-making was Simon (1947, 1957), who through his seminal works argued that human beings were unable to reach the ideal state of rationality due to their cognitive limitations, which would hinder them in making rational choices during the process of evaluating a variety of options. Therefore, Simon (1947, 1957), contended that humans

were only able to exercise rationality to a certain degree, thus. referring to this as ‘bounded rationality’. His arguments were underpinned by the notion that it is highly unconceivable for individuals to always define goals and consider all the alternatives, whilst having the ability to evaluate their potential consequences.

Simon (1957) further argues that individuals lack knowledge, far-sightedness, skill, and time that organizations are useful instruments for achieving human purpose, whilst also stressing the role of information processing and decision making which provided major impetus for further research on organizational decision making and behavioural decision theory. A plethora of researchers across various fields have forwarded a variety of decision-making models as a result of bounded rationality and limited information (Simon 1957; March and Simon 1958; Cyert and March 1963; Hilton 1981). Yet, March (1994) largely places emphasis on organisational decision-making which explores organisations as information processing systems. Accordingly, March and Simon (1958) consider organisations as multi-layered, complex interactive systems, which is made up of the interplay between organisational activities that occur as a result of the systems, and the bounded rationality of the organisational decision-makers within those systems.

However importantly in the context of this research, *A Behavioral Theory of the Firm* (March and Cyert 1963) was published which defines organisations as being manifest with conflicting interests between groupings of various participants and decision-makers, who utilise standard rules and procedures in order to overcome uncertainty in decision-making. Moreover, the researchers exploring decision-making also expressed insights which traditionally sit outside the realms of information processing. The underlying conceptualisation of the manifestation of conflicting interests within organisations provided impetus for studies exploring the role of decision-making from within political dispositions, which emphasises how various organisational actors and groups compete for scarce resources (Pettigrew 1973, 1985; Pfeffer and Salancik 1974, 1978; Pfeffer 1981). Since different organizational groups have different goals, conflict and disagreement arise.

The competition for scarce resources and the pursuit of different goals make the organizational decision making process inherently political (Pfeffer and Salancik1978).

Miller and Wilson (2006), argue that bounded rationality, as outlined by Simon (1957), principally is the consequence of human and organizational constraints. However, it can be argued that this perspective overlooks the part played by power and political conduct in contributing to these organisational constraints. Following this track, a plethora of scholars have alluded to the fact that decision-making is essentially a product of power dynamics, in which divergent sets of organisational actors compete with one another for the control of resources.

For instance, Pfeffer (1981), offers detailed insights into power in organisational settings through his political model. Additionally, Brunsson (1982, 1985, 1989) gives examples of decision-making from political settings through a number of case studies and offers shaded analysis of the decision-making processes and life of organisations that faces conflicting demands. Brunsson (1989) views decision-making in political settings as a process of talking in which organsiational actors participate in, in order to build rationale for actions, form visions of future states, and for the purpose of mobilising resources. He argues that decision-making can play a role in allotting responsibility and creating legitimacy and that decision-making has evolved in that, it is not utilised to coordinate action and ideas, but rather used as a means to face inconsistencies between action and ideas. Thus, it is evident that many scholars were increasingly appreciating the role of decision-making in managing power within organisational settings.

Weick (1969) offers an alternative viewpoint on organisations and their purpose by arguing that, unlike March and Simon (1958) and Cyert and March (1963), who interpret organisations for making decisions, organisations are information processing systems, tasked with minimising ambiguity of information regarding the external environment. Accordingly, processing information and reducing ambiguity of the information is the essence of

organisations. In further development of this notion, Weick and Daft (1983) later view organisations are interpretive systems, whereby the principle for organisations concerns making interpretations. Thus, organisational managers are expected to immerse into a horde of events which are manifest within the organisation, and purposefully attempt to enforce order on them. As such, the interpretation is referred to the process of deciphering these events, developing schemas of understanding and bringing out meaning. As such, within this view of the organisation, the decision-makers are expected to not only process information and interpret it, through certain procedures and guides, referred to as assembly rules, but to also enact it to their environment, thus leading to a collective interpretation. Therefore, the environment plays an important role in the decision-making process, yet is often overlooked when exploring BI decision-making.

2.8 Decision making: Environmental factors

The environment in which managers operate may also impact the way in which they make decisions. Accordingly, it is reported that the approach to governance guides managers according to their sectors to experience dissimilar demands and expectations, which are sufficient to influence their decision making (Yamamoto 1997; Lioukas et al., 1993; Mallory et al., 1983). The responsibilities endowed in each sector essentially differs, yet also dictates how individuals operate and behave, thus also influencing how decisions are made (Chaffee 1985; Hitt, et al. 2003; Mintzberg 1973; Pettigrew 1990).

Accordingly, the environmental characteristics outline the context in which the decision occurs and more specifically can influence the type of decision being made and the pace at which it needs to be made. Thus, when exploring decision-making, the context in which the decision-making process occurs should also be considered. It has been recognised that in order to fully appreciate decision-making, a complete acknowledgement of the nature of decisions is imperative, and once this is achieved, it can help determine the psychological processes and strategies which decision makers use to deal

with decision (Cannon-Bowers et al. 1996). Therefore, considering factors such as social, community, and the work environments, in which decisions occur can be considered as contextual factors (Lizarraga et al., 2009). Flannery et al., (1999) posits that social and work pressures can externally influences the decision-making processes and subsequently its outcome. For example, organisational actors may conform to decisions despite not being in agreement, in order to uphold harmony and avoid being alienated within the group (Rollinson 2008).

Janis (1971) also argues that such social pressures in which organisational actors are pressured to conform to group dynamics essentially confines the thinking of the group, leading to a lack of creativity and cerebral insights generated. Thus, through identifying the role of power dynamics and intra-organisational relationships can help provide insights into the extent to which these affect organisational decision-making. Furthermore, other pressures derivative of the context such as work pressures, should also be factored into the decision-making process (Lizarraga et al., 2009). For instance, the extent to which work pressures in the form of target-driven environments, workload and issues surrounding time constraints are also shown to impact the decision-making process (Van Emmerik 2008). Studies have highlighted time pressures as typically being the result of demands exceeding resource, whereby organisational actors are expected to deliver too much, in a short amount of time (Mauno & Kinnunen, 1999; Nomaguchi et al. 2005).

Accordingly, time pressures can be understood more generally, as having too much to do, within a limited time (Frone et al.1997), therefore, such pressures inevitably have an impact on decision-making, particularly given that they are associated with workload, working hours, the number of work problems, the intra-organisational relationship between worker knowledge, skill, and training and vulnerability to work pressure.

In further exploring contextual factors which may influence decision-making in some way, shape or form, Lipshitz et al. (2001) argue that background knowledge, in the form of experiences and specific roles can be regarded as an imperative decision-making feature. However, Chaudet et al. (2015) argue

that other contextual constraints may also impact complex expert decisions yet are often ignored within decision-making research are ill-structured problems, uncertain dynamic environments, shifting, ill-defined, or competing goals, action/feedback loops, time stress, high stakes, multiple players, organizational goals and norms (Klien et al. 1993). Therefore, exploring both healthcare related social and work pressures may assist in providing insights into the role of contextual factors in impacting BI decision-making.

2.8.1 Public sector decision-making

In current times, due to economic uncertainty, significant curtail of government spending, and the general interest to minimise costs and improve efficiency, public sector organisations been largely favoured for rationalising efforts such as relocation, downsizing and even closure of existing facilities. In such situations, decisions are underpinned by a plethora of factors including the nature of a given service, accessibility parameters and characteristics of the demand. Additionally, the requirement to consider multiple stakeholders further enhances the complexity of social decisions, thus leading to multiplicity of objective challenges which require resolving in an increasingly political environment (Bruno and Genovese 2016). However, there is rising trend in public organisations increasingly opting for BI and related technologies, in order to exploit the tremendous amounts of data captured in their domains (Henkel et al. 2017). Table 2.3 provide an overview of key BI and analytics adoptions within the public sector globally.

Country	Agency	Initiative	Public sector benefits
Australia	Public hospitals	Patient admissions predictive tool	• Capacity management and scheduling.
Brazil	The São Paulo State Transport Agency (ARTESP)	IBM Intelligent Operations for traffic management	• Overcoming traffic problems, optimizing resources and making roads safer.
Germany	Federal labour agency	Application of BI to utilise historic customer data to assist unemployed workers	• Effective use of customer data to assist unemployment which reduces US$15 billion per annum
India	Bangalore water supply and sewage board	Application of predictive analytics in order to monitoring water distribution systems	• Minimising water unaccounted as a result of detecting variations in water flow through real-time monitoring
Japan	Intelligent transport systems	Ministry of Land, Infrastructure, Transport And Tourism	• Resolving traffic congestion, accidents and environmentally degradation through the integration of people, vehicles and roads

Mexico	Government	Disaster management through mobile phone usage	• Traceability of population during spread of epidemic disease
New Zealand	Transportation	Video analytics	• Safer community and more efficient roadways for residents
Philippines	Department of science and technology	Operational assessments of major risks	• Preparing governments for major disasters
Qatar	Hospital and healthcare agencies	Clinical Information Systems	• Proactive analysis of patient healthcare records to predict the likelihood of further complications whilst also offering clinicians risk profiles of individuals from previous medical cases
UK	NHS	Enhanced efficiency through data integration and digitisation	• Reduction of infection rates through integrating and publishing hospital data to encourage and facilitate best practice between hospitals

USA	Internal Revenue Service	Data analytics to detect tax fraud	• Use of analytic methods, tools, and technologies to address such problems as ID theft, refund fraud, inventory optimization,

Table 2.3: Global BI public sector initiatives (IBM Corporation2014; UN Global Pulse 2013)

The way in which decisions are made differs considerably when comparing public and private organisations, as also reflected through research conducted by Rodriguez and Hickson (1995) and Schwenk (1990). Aside from general organisational challenges, private, for-profit organisations are considered to have less troubled and more smoother decision-making processes, whereas public organisations are considered to face more turbulence, disruptions and conflict (Perry and Rainey 1988; Rainey, Backoff, and Levine 1976; Ring and Perry 1985). Many researchers have attributed these dissimilarities to the underlying role and purpose of public and private organisations in society. Private sector organisations typically sell products or offer services to their target markets to generate profits for shareholders. Conversely, a government run entity, funded largely by general taxation, such as NHS Department of Health and Social Care, contracts for services and gathers information relating to the needs of the public. Accordingly, these divergent contexts highlight particularly dissimilar expectations and accountability, which may require different decision-making practices and oversight. Yet, in general, decision-making literature largely fails to account for such differences, thus generalising from one context to the other can be troublesome (Papadakis and Barwise 1998).

According to a number of researchers, the key differences between private and public sector organisations can be largely classified by environmental factors used to describe markets, collaboration and competition, the

obtainability of data and political influence, transactional factors, and process factors (Rainey et al. 1976; Rainey 1989; Nutt and Backoff 1993). Private sector motivations can be described as being fundamentally different to those held by organisations within the public sector, which is largely logical, given their differing environments and contexts. The private sector is characteristically driven by its consumers and market forces, whereas the public sector is more evidently shaped by political attention. While one is about 'business' and 'profit', the other is about 'government' and 'accountability', the former being associated with the decentralisation whilst the latter being more centralised (Perry & Rainey 1988).

Accordingly, these differing environments are suggestive of dissimilar decision content. Although Table 2.4 provides an overview of the key differences between private and public sectors from strategic decision making, Bozeman and Pandey (2004) outline public managers approach to decision-making will notably differ in accordance to the content of the decision itself. Thus, the nature of the content of the decision may also impact how the decision is made, by determining the number of individuals participating in the decision, the time required as well as the decision criteria.

Accordingly, Bozeman and Pandey (2004) differentiate between decision content by dichotomising between technical content which relates to efficiency and effectiveness, where there is consensus regarding goals and political content, which conversely has more disagreement about its ends or goals. Though Bozeman and Pandey (2004) draw on this decision content distinction, this is in line with previous studies which separates between technical and political aspects of organizational decision-making processes (Allison, 1971; Lindblom, 1959; Pfeffer, 1981; Thompson, 1961). Subsequently, political decisions are typically expected to involve more external actors and implicate a higher degree of conflict, with more emphasis on the ends than the means, and on achieving goals. Conversely, technical decisions are largely expected to contain higher levels of economic rationality. As such, it emphasises that decision content is a key factor of decision process and consequently, differing decision processes should be expected across public and private sectors (Bozeman and Pandey 2004; Dillon et al. 2010).

Similarly, Nutt (2006) compares public and private sector decision making through exploring analysis and bargaining metric and finds managers operating within the private sector as more supportive of analysis driven decisions, whereas managers in the public sector favoured bargaining-based decisions. Consequently, this indicates that the public sector is problem-based, whilst the private sector is regarded as being more opportunity based. The sequentially of process within the public sector is also regarded as another key difference; as Dillon et al. (2010) postulate that senior managers in the public sector had the ability to describe activities that had any form of sequential process. Furthermore, it was found that public sector decision-making typically start with a breakdown of objectives and goals. Supporting this, Bozeman & Pandey (2004) highlight dissent and lack of agreements relating to goals is a common feature of the public sector, thus starting with objective definition is expected.

More recent times however have seen the rise of the supposed “New public management” (Dunleavy & Hood, 1994), which refers to traditional public organisations embracing actions which are commonly associated to organisations in the private sector. Consequently, the NPM movement has increasingly led to the decentralisation and transformation of public services, governmental agenices into corporations, otherwise referred to as ‘Corporatization’. A notable feature of the NPM is the implementation of private sector management focus and techniques in the public sector (Hood 1995).

The most notable transformation initiated by NPM is the endorsement of management culture found in the private sector, for public sector organisations, whereby managerial efficiency takes place over the need for effectiveness in the delivery of public services (Self 2000). Furthermore, studies also reveal legitimation-seeking behaviour in public sector organisations, otherwise generally linked to the private sector (Brignall and Modell 2000; Verbeeten, 2011; and Carvalho et al. 2012).

The increasing role of technological advancements in the public sector is also a relevant point of discussion in the extant literature, highlighted by Table 2.5. More generally, ICT in the public sector has mainly been projected as a tool to

initiate new and better service delivery (Bekkers and Zouridis 1999), through providing enhanced efficiency and transparency, and creating better accountability in public administration procedures and management (Dunleavy et al., 2005; Gupta et al., 2008)

In addition to decision content, it is also revealed that organisational actors who had worked in both public and private sectors found the cross-over from one context to the other as difficult and challenging. More specifically, senior managers who built up their competencies and skills base within the public sector experienced the private sector setting as tremendously coercive and unaccommodating. Conversely, managers with a private sector background found the public sector was exceedingly preventive and bureaucratic. Thus, this indicates that managers are most likely to succeed in the sectors in which they build up their skills base. (Dillon et al., 2010)

Decision-maker behaviour is impacted by a number of factors, including external influences and human behavioural factors. The external, contextual factors relate more so to time, both intra and inter-organisational politics, lack of resources in terms of finance and information. Internal influences refers to organisational actors cognition and can refer to a host of factors such as experience, confidence and understanding the domain. Studies also highlight the significance of contextual aspects and human behavioural influences across both private and public sectors, with contextual factors considered less influential in private organisations when compared to public sectors and the human behavioural factors being more influential in private organisations, as a result of the unregulated nature of private sector decision making. Some notable differences between both sectors are further emphasised in Table 2.4, with reference to impact on strategic decision-making.

Classifying factors	Private sector	Public sector	Impact on strategic decision-making
Environmental factor	Consumer buying behaviour defines the market	Oversight bodies form operating market	Decision-makers expected to seek opinions of individuals in oversight bodies in public sector organisations
Collaboration versus competition	competition between firms offering similar services	cooperation between organisations that provide a given service	Shift from competition towards collaboration,
Data accessibility	intelligence data are widely available	limited performance and intelligence data	limited availability and utilisation of resources
Constraints	Legislation and internal consensus only limits autonomy and flexibility	directives and obligations can limit independence and flexibility	the need for consensus increases
Political influence	indirect and internally focused	political influence emanating from authority networks and users	More time and resources required to offset user needs with demands of oversight bodies

Transactional scrutiny	Can isolate the development of ideas	Cannot isolate development of ideas	More transparency and disclosure of differing ideas
ownership	ownership heavily vested in stockholders	general public regarded as owners and enact their expectations regarding the activities of the organisation	shared decision-making and involvement from various people
Organisational process aims	Goals largely clear and unanimous	Fluctuating complex goals, plagued by conflict and divergences	Clarity about the desirability of an alternative declines, increasing the time to make decisions in a public organisation
Authority	Power devolved in authoritative Figures	Stakeholders over authority leaders and can influence control	Searched time and resources more limited

Table 2.4 : Key differences between public and private sectors (Adopted Nutt 2005)

Consequently, it is accepted that there is a difference in assessing IS across public and private sectors (Rosacker and Olson 2008), with majority of studies in this regard being directed towards the private sector (Kolasa 2017; Tona et al. 2012), while studies focusing on public organisations remains limited. It is furthermore emphasised, particularly from the public sector that conflict and dissent is a common practice, particularly given the influence of external actors

and oversight bodies. Accordingly, it is worthwhile exploring how these factors may impact organisational dynamics.

2.8.2 Healthcare BI use

Public healthcare sectors produce exponential amounts of data, mainly consisting of patient records, compliance, and patient care (Raghupathi & Raghupathi 2013), thus offering endless opportunities for healthcare organisations to leverage the vast amounts of information available in new, innovative ways. However, the adoption of information and communication technology (ICT) in health care has been largely seen as an opportunity to not only achieve effectiveness, efficiency, and quality of health services, but also for transparency of the economic activities (Mettler and Vimarlund 2009), to monitor and scrutinise clinical activity (Doolin 2004), help medical researchers and physicians with up-to-date clinical and medical information into research processes, facilitate access to all relevant data across organizational boundaries real-time (Ivan and Velicanu, 2015).

However, there are many challenges associated with BI adoption for healthcare organisations, such as limited access and ability to utilise data collected through non-integrated traditional systems for decision making purposes. Accordingly, Young Lee (2018) stress the importance of empowering both staff and management for strategic decision making through data warehousing based on critical thinking and not merely as a reporting exercise. Given the complexity typically associated with healthcare, studies highlight in order to achieve the full potential from BI use in healthcare, there is a pressing need for the business and analytics strategies to be aligned, for the development of decision-making culture, strong committed sponsorship, and staff who have proficiency in using analytics (Wang et al. 2016; Watson 2014).

Despite such challenges, which are also inherent across other sectors too, BI is becoming increasingly important for the health care sector, beyond just providing information by offering newer ways of working, allowing for the integration of information and organisations and generating measurable

outputs in real time (Mettler and Virmarlund 2009). As also emphasised in the strategy for UK data capability report (HM Government 2013), 'one of the greatest opportunities and challenges facing policymakers today is the ever-increasing significance of data'. Such opportunities of considerably benefiting from data is application across both public and private sectors (ESRC 2012; Beresford, 2015; Mateos-Garcia et al. 2015; Yiu 2012), including the health care, which is advancing further towards digitisation.

In order for successful investment in this regard, it is imperative that organisations have data, which is appropriately captured, exploited and shared across applications, the technical architecture and tools which facilitates the journey of data from capture through to analysis, and finally a skilled and data savvy workforce, which is able to provide an appropriate level of analytical support (HM Government 2013). Yet, particularly from within the UK healthcare context, the latter, i.e. the human element receives the least attention, although it is a critical factor in exploiting the data (Brailsford 2013).

2.9 Decision making: Healthcare contextual factors

In order to understand the context in which the BI is being utilised, it is necessary to examine empirical studies which explore the organisational context and challenges healthcare organisations have faced. Accordingly, Belling et al. (2011) interview 113 healthcare professionals and identify a plethora of challenges across both individual and organisational level. The findings reveal individual-level healthcare barriers such as leadership styles, decision making approaches, unclear professional role boundaries and limited training for personal development. From a more macro perspective, they emphasised public sector healthcare pressures resulting from scarce staffing levels, an overabundance of administrative responsibilities and the disparate nature of IT as key barriers which hinder the organisation. Such challenges are highly likely to impact various aspects of the NHS, including the way in which organisational actors make decisions through using BI. Table 2.5 categorises the key healthcare challenges identified in the extant literature,

therefore providing relevant insights into both social and work pressures which are key constructs as discussed earlier, in understanding decision-making.

2.9.1 Healthcare attitudes and mindsets

Moreover, empirical studies also reveal that a key challenge facing the healthcare organisations related to the attitudes and mindsets of its divergent stakeholders (Russ et al. 2014; Brewster et al. 2013), which range from a lack of conviction relating to organisational processes, stakeholder organisations or the data (Simms et al. 2014; Curnock et al. 2012), to perceived barriers relating to the interpretations between patients and professionals (Shaw and Siriwardena 2014; Twycross, 2013) and resistance from clinicians and managers (Russ et al. 2014; Brewster et al. 2013, McDonald et al. 2005), with an over-emphasis being placed on 'quick wins' as opposed to long-term improvement and development (Davies et al., 2011; Cowley et al., 2002). Further highlighting the implications of organisational actors attitudes and mindsets, it was found that clinical staff and teams across 22 NHS sites were reluctant in embracing online patient support tools as they felt the initiatives of collaboratively reaching decisions with patients was a common practice, which did not require a change of existing routines and that patients were often unwilling to engage in the process. Thus, the lack of benefit of such initiatives can be attributed to the attitudes of the clinicians and managers, whom were tasked with driving this initiative. Furthermore, this also highlights how top-down approaches, commonly associated with the NHS can lead to confrontation and dissonance, due to NHS policy-makers and operational, clinical staff holding conflicting sentiments, attitudes and interests (Elwyn et al. 2012).

Similar to the aforementioned case, whereby clinicians and managers failed to see the benefit of a new way of working, as they felt the current processes were sufficient, it was found that GP's held comparable attitude and mindsets when required to partake in external peer reviews. The GP's felt the ongoing feedback mechanisms were adequate, therefore were reluctant in participating

(Curnock et al. 2012), thus further highlighting the prevalence of attitudes and mindsets as a barrier for NHS improvement.

2.9.2 Skillsets and training

Another key challenge identified from the extant literature relates to the skill sets and training of organsational actors across various facets within the healthcare, such as professionals lacking confidence in their own abilities (Bloe et al. 2009; Hewison et al. 2014), limited skills in implementing improvement initiatives (Maden-Jenkins 2011; Taylor et al. 2014), lack of project and change management skills (McNaughton et al. 2011) and limited analytical skills (Mowles et al. 2010; Williams et al. 2008). Therefore, another factor which may affect the decision-making process are the skills of the organisational actors, particularly given that BI decision-making requires a certain degree of skills for effective use. The exploitation of data, the latest technologies and having the ability to create and act upon actionable insights will remain limited in face of a redundancy in highly skilled and capable analysts who have the ability to manipulate, analyse and interpret data. Therefore, the potential of leveraging competitiveness and effectiveness through the advancements of technology rely on two key factors, the technology itself as well as an adaptive workforce which can adjust to skill requirements and adapt culture (Watchter 2015). Yet, UK healthcare services are facing many challenges in this area (National Information Board 2015). Therefore, alongside skills, the ability to adapt and shift mindset and attitudes within organisations such as the NHS can be regarded as a key challenge, which requires further exploration from within a BI context.

2.9.3 Time pressures and prioritisation

Furthermore, it is reported that time and resource constraints such as financial pressures can also determine how organsational actors organise their activities, as such pressures can also influence individuals to compare results of decisions made with the time and finances expended (Svenson & Maule,

1993). Accordingly, the persistently time pressured environments in which the NHS organisational actors operate within as discussed earlier, is a prevalent theme and one of the key challenges identified in empirical studies. It is widely reported that organisational actors plan their activities and assess the outcome of their decisions based on the time and resources allocated (Greenberg and Baron, 2010). Accordingly, from within the context of the NHS, time and resourcing pressures are widely publicised challenges which continue to create tensions between a variety of organisational actors within a healthcare context. Studies reveal that many improvement initiatives with the NHS are unsuccessful due to organisational actors having limited time to implement improvements (Robertson et al. 2013), or to even reflect on improvements, (Adeodu et al. 2012; Slater et al. 2009) given the pressures of their roles.

In addition to the time constraints, the issue of prioritisation can also be regarded as a major challenge facing organisational actors. With many initiatives driven from the top, as top-down push, results in operational staff, such as managers as well as clinicians struggling to manage their workload, often resorting to prioritising tasks and functions of their role, which they deemed most appropriate (Checkland et al. 2007).Therefore, the policy initiatives set at a higher level in the NHS pursue to privilege organisational priorities and, thus in the process, provide a challenge to professional autonomy and hierarchy (Clarke and Newman 1997). Marshall (1999) also revealed a plethora of NHS specific challenges identified by managers, which included competing priorities for attention of the commissioner as a hindrance across the NHS. Thus, it can be argued that such pressures may also be contributory in how technology may also be used to drive improvements within an NHS context.

2.9.4 Resource challenges

It is also reported that another resource challenge was in the form of staff shortages, whereby there is an increasingly high reliance on agency staff (Bick et al. 2011), thus further adding another layer of complexity, particularly given

the nature of operations within the public healthcare sector. Burnett et al. (2010) further reveal organisational readiness for improvement programmes was hindered due to lack of resources and limited organisational capability. Therefore, further highlighting that organisational actors are expected to commit to initiatives, yet are provided with insufficient support for its implementation, with time and resources being identified as key barriers. This is also reported by Craig (2002), who alludes to the tensions within the NHS created due to 'power' and autonomy being transferred to organsational actors, who may not be equipped, nor capable to effectively deliver the strategic resource shifts.

Additionally, given the nature and scope of the NHS, resourcing is a constant, moving target and challenge for the NHS. It is widely accepted that the NHS lack adequate analytical resources to inform vital decisions relating to health care, across all organisational levels, from individual professionals and patients to the board room. Additionally, it was reported by UK's Chief Knowledge Officer in 2015, that the NHS was '*underinvesting in capability and capacity for the use of data'*, in comparison to the amount of data it produces and collects (Evenstad, 2015). This therefore resonates with the time-bound constraints discussed earlier, whereby NHS organisational actors are expected to deliver more with less. Consequently, by insufficiently investing in BI, many NHS trusts may struggle to produce statutory returns for national and local bodies, while still not having the chance to develop a true analytical capability (Dellenty 2018).

2.9.5 NHS Fragmentation

The NHS is also seen as being highly heterogeneous, largely as a result of its size as an organisation and its subsequent operational depth. The fragmented nature of the NHS is widely reported in the extant literature, across its varying aspects. For instance, structurally, the organisation is regarded as being disparate and silo across services and sectors (Lord et al., 2014; Craig et al., 2002; Larsen et al. 2013), with minimum structural integration of new

processes and the variability of organisational structures also playing a role in the disparateness (May et al. 2003). This may have adverse impact on organisational learning, as being isolated from other NHS organisations and trusts which may face similar challenges reduces the ability for the organisations to learn and share best practice (Marshall 1999). This variability is also evident within the NHS from an information and technology perspective, whereby a lack of information sharing occurred both from inter and intra-organisational contexts (Trebble et al. 2012).

This is further emphasised by Dellenty (2018) who posits that systems have historically and currently remain fragmented across the NHS, consisting of a plethora of localised and home-grown solutions. Kristensen et al. (2013) also posit the NHS mentality of endeavouring to localise all aspects of operations and functions, rather than drawing on wider, regional or national expertise is also a barrier and can be counter-productive. It is argued that this fragmentation is given further impetus because of the dominant disciplinary divide of roles and the tribalism within the NHS, (Brooks and Brown 2002; Bunniss et al. 2012) which is often underpinned by conflicting priorities and obstinate incentives (Whitelaw et al. 2012; McQuillan et al. 2014), particularly between NHS policy makers and NHS professionals (Hanbury et al., 2012).

Therefore, there is little exaggeration in stating that such challenges in face of fragmented sources, systems and ways of working minimise the opportunities for the public healthcare organisations to leverage benefits from their generated data and may adversely impact the healthcare agendas for organisations such as the NHS.

Category	Dimension	References
Initiative-barriers	Application	Checkland et al. 2007; Barnes and Paton 2011; Shaw and Siriwardena 2014; Siriwardena et al. 2014; Russ et al. 2014; Heath et al. 2012; Doyle et al. 2014
	Complexity	Abassi 2018; Brooks et al. 2011; Black 2011; Checkland et al. 2016; Mowles et al. 2010;
Organisational actor factors	Attitudes	
	Clinician / Managerial resistance	Russ et al. 2014; Brewster et al. 2013; Williams et al. 2008; Lawton and Parker 2002; Fear et al. 2003; McDonald 2005
	Limited trust	Curnock et al. 2012; Simms et al. 2014
	Conflicting patient and professional views	Shaw and Siriwardena 2014; Twycross 2013
	Skills and mindsets	
	Lack of confidence	Bloe et al. 2009; Hewison et al. 2014
	Limited improvement approach skillsets	Maden-Jenkins 2011; Taylor et al. 2014;
	Insufficient project management abilities	McNaughton et al. 2011
	Limited analytical skills	Mowles et al. 2010; Williams et al. 2008
	Divergent learning styles	Ramsay et al. 2014
	Time and prioritisation challenges	
	Limited improvement 'reflection'	Adeodu et al. 2009; Slater et al. 2012;
	Lack of time to implement improvement	Robertson et al. 2013
	Conflicting priorities	Pagliari et al. 2012; Checkland et al. 2007

Organisational factors	Resource	
	Reliance on agency staff	Bick et al. 2014
	lack of resources and organisational capability	Burnett et al. 2010; Craig et al. 2002
	Underinvestment in analytical skills	Evenstad, 2015
	Insufficient dedicated funding	Tuffrey-Wijne et al. 2014
	Systems incompatibility	Exton 2010; Robertson et al. 2013;
	Information	
	Lack of intra-organsational sharing	Trebble et al. 2013;
	Limited data use	Scholefield 2007; Williams et al. 2008; Wright and McSherry 2013
	Lack of appropriate IS	Simms et al. 2014; Tuffrey-Wijne et al. 2014
	Fragmented vision and communication	Ross et al. 2014
	Culture	
	Insufficient improvement culture	Berkeley and Springett 2006; Frame et al. 2008
	Blame culture	Ross et al. 2014
	Improvement undermining practises	Brooks 1996; Ramsay et al. 2014
	Localised practises	Kristensen et al. 2013;
	Resistance to externally driven initiatives	McDonald 2005; Millar 2013; Walshe et al. 2001
	Quick-win mentality	Cowley et al. 2002; Davies et al. 2011
	Limited inter and intra-organsational relationships	Craig et al. 2002; Goldie and Sheffield 2001; Rivas et al. 2010
	Silo mentality	Larsen et al. 2013; Lord et al. 2014

Table 2.5: Key healthcare contextual challenges

Popovič et al. (2014) also emphasise the need for organisations to prudently consider the decision environment, in terms of the culture of information use within an organisation, if they are to fully leverage benefits from BI generated information (Işık et al., 2013). Information culture is established in an organisations values, norms, and practices, which subsequently influences how information is perceived, generated and applied (Choo et al., 2008; Oliver, 2003).

The advancements in technology have led to the onset of innovative decision-making initiatives within the NHS, with the aim of enhancing decision-making processes across various stakeholders. For instance, the concept of 'Shared Decision-making' is widely promoted within the NHS and have attracted much interest within healthcare literature (Barr and Elwyn 2016; Barr et al. 2014; Burges et al. 2008; Elwyn et al. 2010; Gravel et al. 2006; Homles-Rovner et al. 2000; Joosten et al. 2008; Joseph-Williams et al. 2014; Joseph-Williams et al. 2014; Stacey et al. 2008; Tai-Seale 2016). Shared decision-making is an approach which promotes collaborative decision-making between clinicians and patients, with the aim of making effective decisions through utilising the best available evidence.

While patients have expressed desire and are highly appreciative of information relating to treatment choices, (Coulter and Magee 2003; Care Quality Commision 2010), a move towards the implementation of shared decision-making has proven difficult due to challenges associated with imbedding the attitudes, skills, and interventions into routine practice (Gravel et al. 2006). Of the key barriers, insufficient time and lack of fit into organisational routines has also been cited (Elwyn et al. 2010).

2.10 Human behavioural factors

2.10.1 BI actors

BI systems can be used to guide and improve decision making at all levels, strategic, tactical and operational (Coman et al., 2010; Paulsen and Coulson 2011), therefore BI users are many, such as Power Users, Business Users, Causal Users, Data aggregators and information providers, Operational analytical users, Extended enterprise users and IT Users (Loshin 2012). However, distinctions need to be drawn between information workers and actual decision makers, who share divergent roles whilst possibly dealing with the same data and information. Chaudhuri et al. (2011) attribute BI decision making to executives, managers and analysts. Therefore for the purposes of this research, information workers, analysts and decision making managers, or any similar roles shall be the unit of analysis for this research. Particularly as the research shall regard analysts as the human processes of the BI systems, who in turn provide insights from the data to the managers for decision making. Therefore, this research regards analysts, information workers and decision-making managers as central to the continuous process of BI decision making.

Love (2007) mentions BI at the higher level of an organisation deals with all areas of intelligence, including Market intelligence (MI) and CI. Whereas, having the knowledge of what occurs within the business is BI at the lower levels. Therefore active use of BI is not solely for highly ranked employees of the organisation. Consequently many organisations are pursuing BI more pervasively, with BI becoming accessible to more people, such as operational staff, suppliers as well as customers (Wixom and Watson 2010), no longer only by specialists.

Figure 2.5: Organisational hierarchy

The tactical levels utilises BI to convert long-term strategic decisions into operational metrics, whereas the operational tier uses BI to support daily operational needs, via the use of timely, data-centric information. Thus, allowing for measuring and monitoring performances to take place (White, 2007). The strategic level use of BI is for the purposes of strategic, value adding decisions that contribute towards supporting long-term corporate goals and objectives (Pourmojib et al. 2013).

While key BI users have been identified, unlike organisations in other sectors, it must be noted that healthcare is made up of diverse set of actors, which in turn also includes diverse set of BI users, who may contribute towards the BI decision-making process in different ways, give that BI is used to support both administrative and clinical decisions (Gaardboea et al. 2018). There is a long-established practice within healthcare to incorporate data which sits beyond the traditional parameters of a single organisation, for an appreciation of medical, business and facilitating processes (Scott 2002), thus incorporating a plethora of individuals including external factors such as suppliers, other health care organisations and governmental authorities (Mettler 2008).

Although such stakeholders who may have the ability to externally exert influence, through the information they provide, they cannot be deemed as active users of the BI systems. Therefore, in such circumstances it is argued that the internal actors, such as the functional managers, analysts and clinicians are active users of BI, each taking up roles such as the Power Users,

Business Users, Causal Users, Data aggregators or information providers (Madsen 2017). However, there has been a more recent drive internally, within the NHS to develop, information / data analysts who are able to dedicate their time entirely to providing actionable, timely data (Howard et al. 2015).

2.10.2 Cognition

In addition to the earlier discussions relating to the movement away from rational decision-making towards more of the behavioural aspects pertaining to decision-making, such as organisational actors cognition, it is worth highlighting that such insights have received limited attention from within BI decision-making literature, thus worth exploring. While decision-making in general has been a relevant point of discussion across many disciplines, such as psychology, management, public administration, politics and for various sciences (Filiz and Battaglio 2017), with studies focusing on both organsational and group decision making (Simons et al. 2016; Csaszar et al. 2013; Carrasco et al. 2016; Luoma 2016; Liu et al. 2019; Zhu et al. 2014; Marshall et al. 2017), it is argued that decisions may differ according to their nature, of whether or not they require deliberation or are made more spontaneously (Small and Sukhu 2016). Therefore, decision making can be considered as a dynamic and often iterative process, largely influenced by a number of factors, which include the nature of decision, the nature of the individuals involved and the environment in which the decision is being made. As such it is important to consider the subject or organisational actors characteristics, which may include their internal factors such as motivation, vital information processing, expertise, and the sentiments which are an inherent aspect of any decision (Lizarraga et al. 2009).

The processing of decision-related information brings with it many challenges, with it either involving numerous attributes, or the fact that more than a small amount of information can overwhelm the cognitive capacity of decision makers (Cowan 2010). Decision makers are expected to assess the relative importance of each attribute, which can prove to be difficult when factoring in

the tradeoffs between certain attributes. Thus, this illustrates the cognitive challenge individuals may face when trying to make a decision.

It has previously been outlined that cognition plays an active role in decision-making processes (Newell and Simon 1972). Studies have revealed, in contrast to the rational approach outlined earlier, that organisational actors with decision-making duties are often encountered with a number of challenges, such as not having sufficient time which allows them to learn choice alternatives, a lack of working memory, and partial computational capabilities (Miller 1956; Payne et al.1993) Accordingly, organsational actors rely on heuristics which in turn, enables information-processing demands of a task within the boundaries of their restricted cognitive capacities. Factors such as cognition is overlooked when exploring BI decision-making, this can be troublesome, particularly as cognition can assist individuals to process information, cogitate steps to be taken, and overcome difficulties which may arise during the decision-making process (Mellers et al.,1999).

More recent times have seen the rise the trend of focusing on non-cognitive skills and abilities (Heckman and Rubinstein 2001, West et al., 2016). Unlike cognitive skills, non-cognitive skills can be considered as not directly being associated with the process of obtaining knowledge through the senses, experience or reasoning. Alternatively, non-cognitive skills can be considered as behaviours, mindsets, attitudes, learning strategies and social skills which can potentially have considerable impact on the way human beings learn. Although this research is firmly embedded in a management focus, not from a psychological disposition, given the exploration of organisational actors and their cognition, it is still imperative to also acknowledge the psychological frontiers of this research. Given that both ‘noncognitive’ and ‘cognitive’ are commonly juxtaposed together, this research in line with Borghans et al. (2008), abstains from referring to ‘noncognitive’ as a term to describe personality traits. Drawing on the distinction between cognitive and noncognitive can be disconcerting, particularly given that almost all aspects relating to human behaviour are cognitive. Taking the view of Borghans et al.

(2008), this research acknowledges personality traits of organisational actors as patterns of thought, feelings and behaviours.

Recent studies have also investigated how emotions may play an active role in decision-making. With reference to emotions, Slovic et al., (2004: 312) argue not just prominent emotions such as fear and anger, but also 'faint whispers of emotions' referred to as 'artefacts' are very relevant within decision-making context. Therefore, seemingly purposeful and calculated decisions may not only be made by carefully processing information, but also as a result of intuitive judgement of how certain outcomes may feel (Lerner et al. 2015). Studies highlight that this may also be prevalent despite the availability of numeric information in regard to the possibility of certain events (Denes-Raj & Epstein 1994; Windschitl & Weber 1999; Slovic et al. 2000)

Still highly related to this idea of cognitive decision making is the widely accepted notion that some individuals experience the world as swift, intuitive, automatic and unconsciously, whereas on the contrary, others experience it, as slow, analytical and deliberate (Evans 2008; Kahneman 2011). Accordingly, the key characteristic of affection underpins the intuitive, reflexive system through which individuals experience the world (Espstein 1994), as it is the affective responses to stimulus which ever so often are the first responses and connotations individuals have. Thus, by determining what is important in certain circumstances, drives the processes which follow, like information processing, that are essential to cognition (Zajonc 1980).

Recent studies however, have merged insights from dual process theory to gain an understanding of actions which may not only be either deliberate or automatic, but both (Vaisey 2009). Studies have also investigated how automatic and deliberative processes influences the way in which individuals 'frame' for sense-making of certain cirucmstances (Esser and Kroneberg 2015). Although there is divergence between scholars regarding the dual process model, and whether automatic and deliberative processes, are antithetical or have more in common (Leschziner and Green 2013), it can be considered as a beneficial approach for exploring behaviour.

2.10.3 Actor skillsets

For BI success, organisations are required to link BI with their business strategies (Viaene 2008), strategic vision (Bartes 2012) whilst also embracing BI driven organisational culture and capabilities (McAfee and Brynjolfsson 2012). The skilled decision-making managers and analysts are also key components, though often ignored (Shanks and Sharma 2011). Therefore, the purpose of BI is not only limited to the realms of data complexities and information sharing but rather BI also has the role of converting 'data into useful information and through, human analysis, into knowledge' (Negash 2004: 180).

Supporting this further, Sharma et al. (2014) emphases the role current technologies have played in making structured and unstructured data available for managerial decision-making. However, in order for insights to surface merely possessing plentiful information, raw data and analytical tools at ones disposal is not sufficient. There is the need for active involvement between all the entities to unravel the relevant insights which in turn, lead to knowledge. Sharma et al. (2014) suggest that 'first order effects' of analytics are most likely to impact the decision making processes, therefore the superiority of organisational performances are a possible result of superior decision making processes initiated by decision-makers.

It is therefore unanticipated that, while the extant literature identifies the integral role of organisational actors and decision-makers from within the BI context, this area for BI research is understudied. McAfee and Brynjolfsson (2012) support the idea that, though technology has enabled the use of powerful, complex and useful systems, the power of BI technologies does not negate the need for 'vision or human insight', therefore paving the way for further BI focus towards these elements. Studies do indicate however, a drive towards making BI more pervasive (Wixom and Watson 2010), with the operationalisation of BI workload (Hosack et al. 2012), and more BI emphasis at the lower level of the organisational hierarchy (LaValle et al. 2011), nevertheless, this prospect presents challenges. Barton and Court (2012)

posit the challenges of making data analytics and BI trustworthy and digestible for all employees, highlighting from a retail industry context that employees do not rely or understand BI. Therefore it is proposed that more needs to be done, to disseminate 'expert' level analytical skills to others in the organisation (Shah et al. 2012). Particularly as Sharma et al. (2014) attribute the process of triggering organisational insights to numerous actors from the organisation.

This research therefore explores BI from a decision makers perspective, though differing from previous decision centric studies by focusing mainly on the professionalism and competencies of BI analysts and decision maker(s). Although BI literature has largely been dedicated to the technology, the BI users who are overlooked are arguably the prerequisites to BI success. Matthias et al. (2016) posit that in reality it is a matter of skills, rather than merely technology. The rise of BI has led to increased demand for advanced BI users. McKinsey Global Institute stress the importance of BI users expertise in deep data analytics (Manyika et al. 2011), whilst Chen et al. (2012) propose skills in managing, descriptive, predictive, and prescriptive analytics. However this requirement is met by an ongoing talent gap and shortage of skilled workers which is hampering organisations BI success (Russom 2011; Watson et al. 2013).

Furthermore it has been forecasted that by 2018, the US will face a deficiency of approximately 140,000 to 190,000 skilled BI users with deep analytical skill-sets, as well as a shortage of around a staggering 1.5 million data-shrewd managers with the big data analytical know-how required to execute, competent, effective decisions (Manyika et al. 2011). Additionally, the study of Olszak and Ziemba (2012) highlighted that in order to derive success from BI, its users should regularly develop decision-making processes whilst recognising their requirements. In addition, the knowledge and skills of BI users and personnel were also highlighted are paramount in BI success. Supporting this, Masaros et al. (2016) found that forming a BI team that consists of qualified BI users with previous experience of BI implementation and use leads to increased BI success rate in organisations.

Although a plethora of studies establish that advanced skillsets is a significant precondition for attaining value from BI, Miller (2014) suggests there is no agreement between writers on what new skills are required. Conversely, Yeoh and Koronios (2010) highlight non-technical, organisational and process related factors as being more pertinent to BI success than technical, data related elements. Contributing to this, Davenport (2010) also emphasises many non-technical factors that contribute to the development of analytical capabilities, whilst also stressing that it is not always about 'datafication', rather consulting and human factors which are often undervalued are equally as important, with large outlets such as IBM and Accenture embracing the non-technical, analytical consulting capabilities. Mainstream media has also reported that over 100 analysts diagnosed with development coordination disorders (DCD) and dyslexia have been employed by the British Intelligence Service (GCHQ) due to their abilities of recognising patterns and skills in analysing complex data otherwise (Philipson 2014).

Non-technical attributes such as intuition, creativity and the faculty to form new ideas innately that typically are not highly appraised in BI environments have been purported as being the solution to deriving insights from BI (Manyika et al. 2011). Therefore, these non-technical elements will be examined in this research. McAfee and Brynjolfsson (2012) report when data conflicts with intuition, a number of senior decision makers are now overriding their personal intuitiveness in a bid to become more data-driven. However, by large people continue to rely heavily on internalised experience and intuition and not enough on data (McAfee and Brynjolfsson 2012).

Therefore the research attempts to assess how BI users and decision makers strike this balance, and explore what role personal intuition plays in overcoming, and perhaps exceeding technical skills that are reportedly required during interactions with BI systems. Particularly as Philipson (2014) expresses that new insights are more likely to be produced through employees levels of curiosity that generates new streams of exploration as opposed to merely depending on technical tools and algorithms. Although studies have recognised the central role of BI users in contributing to overall BI success in

organisations, by identifying ‘the right team of BI workers’ as a key success and considering them as prerequisites to success (Olszak and Ziemba 2012; Shanks and Bekmamedova 2012; Masaros et al. 2016), the extant research dedicated to BI user focus remains peripheral.

Although decision makers with the appropriate access to high quality information is vital for BI system success (Yeoh & Koronios, 2010), it must also be noted that organisations lack IS skills and knowledge to effectively utilise decision-support information (Ramamurthyet al. 2008) Popovic et al. 2012), also emphasis the fact that organisations should develop the necessary IS skills and knowledge in order to progress and make effective use of BI capabilities. However (Foshay and Kuziemsky, 2014) identify that it is not just IS skills that are required, but it is also imperative that management personnel possess data analysis skills and that processes are in place to enable effective dissemination of information.

2.10.4 Personalities

Studies are increasingly exploring the relevance of personalities, attitudes and mindsets in relation to human and social capital and workplace outcomes. For example, Yang et al. (2011) reveal that a proactive personality is positively linked with interpersonal helping and negatively connected with turnover intention, thus suggestive that organisational actors are less likely to leave due to them being socially embedded within the organisation. Thus highlighting how personalities may have a significant implication on internal social networks and therefore on organisational dynamics.

Many aspects of personality are influenced by cognitive processes, with an increasingly body of literature emphasizing the role of individual organisational actors personalities in decision-making. For instance Almlund et al. (2011) explore link between personalities and economic decisions associated with risk and time preferences, as well as other cognitive aspects such as trust, mutuality and philanthropy. Previous studies have highlighted the role

personalities play in the decision-making process, with Filiz and Battaglio (2017) revealing that personality can also have an influence on decision-making according to social, cultural and organisational environments.

Many psychologists have attempted to define what constitutes personality, with some positing that expectation, motivation, goals, values, and interests are not dimensions of personality, whilst others have argued that if such dimensions are prevalent over periods of time, they can be regarded as falling within the confines of personality (Costa and McCrae 1988). Therefore, it can be argued that personality, as a theme is rather loosely understood, with varying views on what it does or does not represent. Therefore generally, personality and individual differences relates to all aspects on which individuals contradict one another. Thus, in line with Borghans et al. (2008), personality traits can be referred as patterns of thought, feelings, and behaviour and in line with their understanding, through focusing on individual differences in how organisational actors actually think, feel, and act, not on how people want to think, feel, and act

As such, personality can be considered as a key characteristic which impacts decision-making and also managerial performance (Hogan et al., 1996). Defined in many ways, personality can also refer to the traits, thought models, behaviours and feelings of individuals (McAdams, 2008). McKinney and Howard (1998) argue that through placing emphasis on individuals, specifically managers, can help unlock pertinent insights into organisational decision-making. Accordingly, through exploring how divergent organisational actors' personalities may play a role in how they use BI will assist in improving our overall understanding relating to BI decision-making from a cognitive context.

2.10.5 Actors intuition

In further opposition to the rational decision-making approach previously highlighted, it is argued that organisational actors many not opt for a rational approach, but rather rely on judgements, negotiations and their intuition in

reaching decisions (Klein et al. 1993; Dane and Pratt 2007; Langley et al. 1995; Bazerman and Moore 2008). Such approaches to decision-making are heavily underpinned by experiences, personal beliefs, and the innate processing of situations for decision-making.

The concept of intuition is also one that has attracted much interest from within organisational decision-making contexts, particularly its role in managerial and organisational cognition as an alternative approach to decision making. Intuition, though synonymously with other terms such as 'gut-feeling', 'insights', can be described as an automated processing style which allows decision makers to rapidly process large quantities of information, without consciously acknowledging the occurrence of this process (Dane and Prat 2007; Hodgkinson and Starbuck 2008). Furthermore, intuitive decision-making varies from rational decision-making in that decision makers do not take all the alternatives into consideration, rather they correspond or recognise patterns or instinctively accumulate cues which directs them to the right alternative instantaneously, with little if any effort. However, a major drawback of such approach when compared with the rational model is in the inability of organisational actors in conveying and justifying their intuition-driven judgments to other organisational actors (Klien 1998).

Therefore, as expected, there is much divergence between writers on whether intuition should be endorsed or discarded within an organisational context. For instance, the instinctive hastiness in applying a pattern to a phenomenon is argued to interrupt or significantly limit an individual's or a group's thinking too quickly (Bonbeau 2003). Similarly, philosophers have also taken such position, by contesting that intuition-talk is a bad practise (Williamson 2007*), as 'intuition is a kind of intellectual/verbal virus (or tick) that started spreading about thirty to forty years ago. It is a bad habit and we should abandon it…and there's no semantic anchor point and the term ['intuition'] fails to have a semantic value' (*Cappelen 2012:50). Conversely, others have argued that despite criticisms levelled towards its semantic value, if intuition is able to achieve a helpful pragmatic contribution, then it should be considered as a good habit (Andow 2017).

Klein (1998), explores the role of intuition more closely and posits that intuition is driven by 'experiences' which help identify key patterns that assist decision-makers in making sense of the dynamics of a given situation. Moreover, the field of Naturalistic Decision Making (NDM) has contributed much to discussions pertaining to the role of intuition within decision-making contexts. Studies revealed that in natural settings, organisational decision-makers heavily rely on intuition when making decisions (Klein et al., 2010, Klein et al., 1993), therefore leading to further focused studies which explored the importance of intuitive decision-making. As such, Klein (1998) associated intuition with expertise as it is derived from experiences, thus referring to expert intuition. The literature pertaining to intuition consists of several perspectives. Nonetheless, intuition is a widely recognised as a phenomenon that describes a gut feeling or inherent impulse which enlightens judgments and decisions (Blackler and Popovic, 2015; Fischer et al. 2015). According to Salas et al. (2010: 966) *'knowledge-based intuition can be acquired through experience'*, for the purposes of this research intuition based on experience is relevant and of interest. Salas et al. (2010) draw distinctions between the expertise-based intuition and general intuition, which is depicted in the Venn diagram in Figure 2.6:

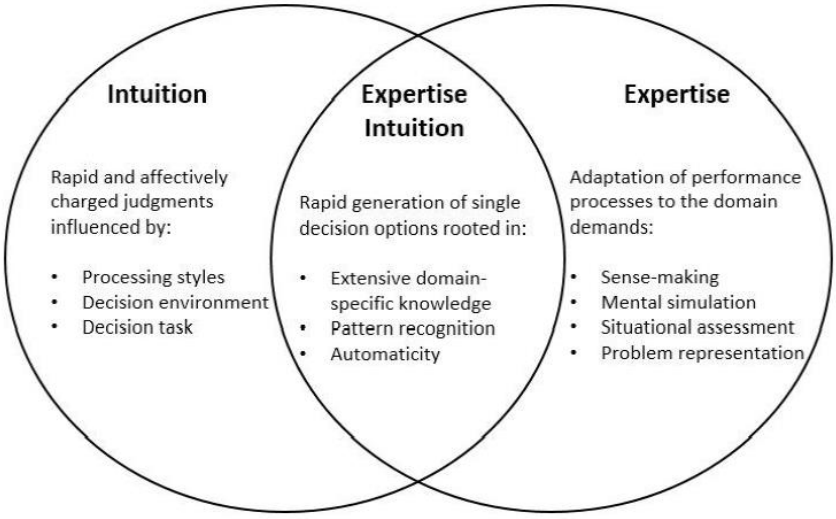


Figure 2.6: Expertise-based intuition (Salas et al., 2010).

The level of intuition required in analysis by decision makers is dependent on the type of decision being made (Hostmann et al., 2007). Although organisations are increasingly preferring fact-based decision making rather than gut feeling, (Watson and Wixom, 2007), decision makers continue to engage in intuitive decision making when things seem out of the ordinary (Harding 2003; Salas et al., 2010). Research suggests that organisations that rely on hard data as opposed to personal intuition for decision making are likely to succeed in their BI initiatives (Eckerson 2003; Howson, 2008; Sabherwal and Becerra-Fernandez, 2010). This it can be argued is problematic, particularly during the contestations and negotiations that occurs between actors (See section 3.7.1) as actors may encounter difficulty in sharing or communicating their intuitions that may not be immediately defensible in a rational sense (Salas et al. 2010), particularly in 'indeterminate situations' whereby there is no consensus between actors (Kuhn and Jackson 2008).

More generally, Epstein (1994:710) argues of an extensive evidential base in everyday life, that people on a daily basis are cognizant of reality in dichotomic ways, one largely being viewed as intuitive, automatic, natural, non-verbal, narrative, and experiential, while the other being more analytical, deliberative, verbal, and rational. In judgment and decision making contexts, the former which emphasises intuition refers to 'System 1' whereas the latter, in reference to analysis refers to 'System 2' (Kahneman 2003). Yet, Hammond (1978, 1996, 2000) opposed the notion that both intuition and analysis are even 'rivals' forms of knowing, and probed further the widely accepted view that judgement and decision making need to be either intuitive or analytical. As such, the dual-process theories have been largely negated, barring Epstein et al., (1996), for their lack of insights into how both systems (intuitive and analytical cognitions) may interact. Most dual process advocators are seen to have considered both the intuitive and analytical cognitions as being dichotomous and in competition with one another, with little insights into their relationship. In disproving this false dichotomy, Hammond's (1996, 2000) Cognitive Continuum Theory (CCT) offers a wide-ranging view of cognitive modes that are situated between intuition and analysis. The CCT also outlines the relevance of the interaction between cognition and the task for judgment

and decision making and highlights that the extent to which intuitive and analytical processes are applied ultimately depends on a variety of factors such as the complexity of the task structure, and the availability of information and time. Thus, with limited time and with poor task structures, decision-makers are expected to revert to their intuitive judgements, as opposed to more analytical approaches. Therefore, ultimately the contextual factors, such as decisions types is seen to influence whether decision-makers rely on intuitive or analytical processes.

Accordingly, it is also argued that for decisions which do not have explicit solutions, BI allows the decision makers to apply intuition in the decision-making process which is beneficial in such circumstances, resulting in a greater degree of success (Harding 2003). Furthermore, Shollo and Galliers (2016: 357) posit that *'BI systems make it possible to articulate hypotheses that might arise from intuition, gut feeling or previous beliefs and experiences, based on a selection of data that may not have been available previously'.* As outlined by Kahneman and Klein (2009:525), *'a psychology of judgment and decision making that ignores intuitive skill is seriously blinkered',* therefore, by acknowledging the role of intuition in decision-making within the context of BI, will offer further insights into how the systems are used by organisational actors and whether BI systems triggers intuitive processes.

2.10.6 Actors curiosity

Curiosity is a widely researched phenomena, as such, many academic studies identify curiosity as a drive, personality trait and motivation to explore (Garrison et al. 2008). Furthermore, James (1950) also views curiosity as a personality characteristic, describing two variations of curiosity, the first being the "*susceptibility of being excited and irritated by the mere novelty of….. the environment"* and secondly scientific curiosity directed more towards specific items of information (James 1950:430), although it is argued that the distinction between both is rather superficial, it resonates with earlier views of

curiosity, of being an intrinsically motivated desire for information (Blumenberg 1983; Loewenstein 1994).

The role of experience in the build-up of intuition, otherwise known as 'expert intuition' is extensively highlighted by NDM researchers (Klein & Hoffman, 2008; Klein et al., 2010, Klein et al., 1993; Klein, 2004), from a decision-making context and given that studies have alluded to decision-makers heavy reliance on intuition in natural settings, much effort has gone into strengthening intuitive organisational decision making (Klein 2015). However, experience is not always readily available, nor guaranteed for organisational actors. Furthermore, it is also highlighted that although experience and background knowledge may play a pivotal role in decision-making (Lipshitz et al., 2001), such skills and experiences may not be transferable in other contexts (Singley and Anderson 1989). Such instances presents further complexity within the decision-making process, whereby organisational actors find themselves in unfamiliar real-world organisational problems, which requires exercising a degree of creativity to overcome (Chaudet et al., 2015).

Accordingly, such creativity can be referred to as having the originality and capability of applying new solutions to a given task and situation (Sternberg and Lubart 1999). Harvey et al. (2007) outlines that organisational actors, particularly managers with a lack of experience and limited formal training necessitates the need for 'curious' managerial mindsets.

This curiosity and creativity dyad can be characterised through two underlying features of human nature, the first being the drive to learn and explore (Kashdan and Silvia, 2009), the other being the drive to create things that are new and valuable (Amabile, 1983, Amabile, 1988, Oldham and Cummings, 1996, Woodman et al., 1993, Stein, 1974). While studies have generally acknowledged the role of curiosity in pursuit of information, this phenomena has been further theorised and categorised as being either diversive or specific (Nishikawa & Amemiya 2016). Diversive curiosity refers to the wide-ranging desire in exploring and learning, whereas specific curiosity involves the motivation to solve a particular puzzle (Berlyne, 1960, 1996, Loewenstein,

1994, Litman and Spielberger, 2003, Litman and Jimerson, 2004, Litman et al., 2005, Harrison et al., 2011). Moreover, it is argued that such creativity, in absence of experience can be attained through specific curiosity, which through idea linking nurtures creativity (Hagtvedt et al. 2019).

Essentially a topical discussion within psychology research, curiosity has been identified as a significant motive which influences human behaviour (Berlyne 1954, 1966, 1978; Engel 2011; Gottlieb et al. 2013; Hebb 1955; Kang et al. 2009; Piaget 1969). Thus, in response to the rational decision-making approach and from within a decision-making context, it is argued that curiosity can be understood as the ambition of reducing information gaps, which effectively is the difference between '*what one knows and what one wants to know'* (Loewenstein 1994:87), thus profoundly impacting decision makers, given their reliance on basing decision on incomplete information when deciding among alternatives (Baharlou 2017). The relevance of curiosity from a decision-making context is further explored by Baharlou (2017), who develops a model of choice with curiosity using Loewenstein's interpretation of curiosity.

Accordingly, the extant literature widely acknowledges the role of curiosity in decision-making, with it attributed to creativity and in general, its pursuit of information, particularly when organisational actors face making decisions with incomplete or partial information. However, the role of curiosity as a characteristic of organisational actors remains largely overlooked within the BI decision-making process. It can be argued that technological advancement such as BI tools, may have the opposite effect in that, it may enable organisational actors to not only fill any information gaps, but also offer an additional layer of insight based on the available information as a result of the forecasting capabilities of the tools. Although Arnone et al. (2011) investigate the role of curiosity, interest and engagement from a technology-pervasive context, they largely explore this from within learning educational environments, not from an organisational decision-making context. Therefore, how curiosity may be exercised by organisational actors through the use of BI is a relevant point of discussion.

2.11 Technology-Human lenses

While it is appreciated that decision-making has been explored for many decades, through varying lenses, it however requires closer attention, principally due to the technological advancements in recent times. Studies have previously indicated that broadly speaking, the manifestation of technology in organisation studies is scarce (Orlikowski, 1992; Orlikowski and Iacono, 2001), and exploring the interplay between technology and actors remains a key challenge (Karanasios 2018).

As highlighted by recent studies, it is argued that this issue is further contributed by trends which show IS studies overlooking technology (Cecez-Kecmanovic *et al.*, 2014; Sarker *et al*., 2013). However, it must be noted that this has not been neglected completely. There are a variety of concepts which help explore how individuals make sense of, practice and incorporate IT into their working practices (Koch et al. 2013). For instance, at an organisation wide level, theoretical concepts such as structuration theory (DeSanctis & Poole, 1994; Jones & Karsten, 2008), innovation theory (Swanson, 1994; Swanson & Ramiller, 2004), organizational learning theory (Huber, 1991) and organizational change theory (Markus & Robey, 1988) have provided much insights into how and why organizations integrate IT into structure and processes. Similarly, Human-centric concepts and theories and IT practice-in-use have enhanced our knowledge relating to how humans retort to and enact technology in their daily organisational lives, which on occasions can result in expected as well as unexpected consequences (Orlikowski, 2000; Boudreau & Robey, 2005; Vaast & Walsham, 2005). These latter theories are largely oriented to understanding the changes that occur through the situated use of IT by individuals, who choose to appropriate features of an IT that fit their situation while ignoring others features of the IT (Vaast & Walsham, 2005).

2.11.1 The Structurational Model of Technology

Although the amalgamation of technology alongside human and social capital has long been ignored in the academic literature, some studies have offered relevant insights into this. For instance, the Structurational Model of Technology places emphasis on the duality of technology (Orlikowski 1992). Accordingly, technology is viewed as an output of human action, such as design, development, appropriation, and modification. Technology can also be considered as a medium of human actions, whereby it is enabled and forced through interpretive schemes, such as categories and assumptions, facilities, land, buildings and technology and norms in terms of codes of conduct and etiquette. The organisational environment in which the technology is used has the ability to impact the way in which the organisational actors interact with it. Accordingly, the outcome resulting from this interplay impacts institutional properties of an organisation by strengthening or modifying structures of signification, domination, and legitimation. Consequently, IT can be considered as socially constructed by its users, who choose and highlight some of their properties.

On the contrary, the characteristic of the technology can also influence how actors may operationalise the technology and what they may use the technology for. This is further emphasised by Orlikowski (1992: 406) who posits ‘‘*technology is physically constructed by actors working in a given social context, and technology is socially constructed by actors through the different meanings they attach and the various features they emphasize and use. However, it is also the case that once developed and deployed, technology tends to become reified and institutionalized, losing its connection with the human agents that constructed it or gave it meaning, and it appears to be part of the objective, structural properties of the organization”.* DeSanctis and Poole (1994) were of the view that earlier structuration models failed to completely describe situations ensuing from the implementation of advanced information technologies (AIT). There are two central concepts for adaptive structuration theory (AST): structuration and appropriation (DeSanctis and

Poole 1994). These theoretical constructs focus on the dynamic nature of technology adoption and use in organisational contexts.

Thus, Orlikowski's (1992) structuration model of technology focuses on the technology, and views it from the context of structuration, as a structural property of organisations. It can be argued that certain organisational decisions are executed based on rationality in an automated process, the organisational actors who rely on BI tools that support their ongoing practices, thereby are enacting structures which shape their emergent and situated use of the technology (Orlikowski 1992). She further outlines that technology only has the ability to impact an organisation through the appropriation of organisational actors, although it is a medium of human action. This is achieved through constraining and enabling, hence conditioning social practices. Therefore, the extent to which interactions with the BI tools may allow organisational actors to learn and gather deeper tacit knowledge which in long term will make them more intuitive and effective is a relevant point of discussion (Orlikowski 1995).

These cognitive influences play a role in deciding which data elements are chosen to describe a given phenomenon, whilst also influencing what trends and relationships connected to the data elements are deduced. These insights may thereby be applied by the analysts and managers to entwine an account making sense of the world, which lead to actions that bring the interpretations to light explicitly. Although Shollo and Galliers (2016) exhibit the cognitive workings of decision makers in their study, the capabilities of BI tools are continually advancing. Lycett (2013) argues that BI tools allow for trends, relationships and patterns to be detected, however insights into what causes the patterns to occur has to be understood by individuals in order for value creating actions to be undertaken.

Sharma et al. (2014) also highlights that in some instances these computerised algorithms are not only used to detect trends but to also execute decisions and actions, such as in the case of credit card fraud detection and computerised stocks trading. This resonates with the decision-making

relationship Davenports (2010) describes in his framework as ‘automated decisions’. Lycett (2013) similarly describes this functionality for Netflix’s recommendation algorithm. Nevertheless, regardless of automated actions, the human insight still plays a role in firstly accepting the machine generated decisions as being valuable and relevant and secondly whilst determining whether these machine learning decisions should be deployed in an unguided automated manner.

2.11.2 The Technology Enactment Framework

Additionally, The Technology Enactment Framework (TEF) is considered as appropriate lens through which technology and human interactions can be explored. IS researchers are increasingly using the Institutional theory to understand the complex interplay which plays out between IT, social and organisational factors. Accordingly, the TEF is widely touted as a beneficial analytical framework too in this context (Cordella & Iannacci, 2010; Luna-Reyes & Gil-Garcia, 2011). The TEF can also be regarded as being relevant in the context of this research as it also draws on institutional theory, governance and bureaucracy thus providing a suitable structure to explore the relationships between technology and organisations, and how organisations enact aspects of the technology in consonance to their social, cultural, and institutional features (Yildiz, 2007). Elements of the Institutional theory offers appropriate direction to examine the intricacies of ‘bureaucratic politics amid network formation and technological change’ (Fountain, 2001), stressing how political agendas, organisational characteristics, such as the role of bureaucratic dynamics within organisations, and pre-existing arrangements in terms of cognitive, cultural and socio-cultural and legal dimensions, form the process of ICT implementation (Cordella & Iannacci, 2010; Wonglimpiyarat, 2014).

The framework suggests that objective information technologies can be altered through organisational and inter-organisational influences to become enacted technologies (Antonio Cordella and Iannacci 2010; Gil-Garcia 2006;

Herrera and Gil-Garcia 2010; Lee et al. 2009; Luna-Reyes and Gil-Garcia 2011; Tsai et al. 2009; Yildiz 2007). Distinguishing between both, objective technologies refers to the range of IT software, hardware, network and the Internet, whereas enacted technology refers to the actual use and perception of technology in a given setting.

According to Fountain (2011), objective technologies are all the features of a technology, which can possibly be used, however for whatever purposes, are not actually used (Gil-Garcia and Luna-Reyes 2009; Gabriel et al. 2004). Thus, it is argued that two aspects could represent the enacted technology, firstly the technological features of the current system as well as the way different organisational actors leverage benefit from the technologies characteristics (Hassan and Gil-Garcia 2008). Put more plainly, Fountain (2001:88) posits '*the embeddedness of government actors in cognitive, cultural, social, and institutional structures influences the design, perceptions, and uses of the Internet and related IT'.* Due to the interplay of these factors, the enabling technology is modified into an 'enacted' social environment, whereby the technology is used by organisational actors in disparate ways which best suits their organisational needs.

The concept of 'enactment', initially articulated by Orlikowski (2000), identified managerial opportunities to 'translate' ideas and sense-making into practical objectives. This is further emphasised by Boudreau and Robey (2005) who posit that features of the enactment process are related to agency theory whereby human 'actors' strive to achieve certain outcomes. The central premise of enactment concerns the behaviour of managers who are influenced by existing social norms, which is reflected through their actions to institutional occurrences and structures (Feldman, 2004).

Furthermore, Chan et al. (2011) highlight that enactment is dependent upon the contextual setting, as managers act in response to a wide range of organisational demands. In the context of this research, given the importance of understanding how technology is being used and operationalised, therefore, the research explores NHS challenges as reported through empirical studies as a means to provide the contextual aspects relevant in uncovering impact

on how technology is enacted by various organisational actors. Notwithstanding the criticism drawn towards the enactment framework, researchers have also expressed the benefits of utilising the enactment framework.

For instance, Bretschneider (2003) stresses that this framework is highly beneficial as it aims to understand more closely the interrelationships between technology, organisations and institutions. In support of this, Dawes (2002) also highlights that this framework is of much relevance and can contribute to practical implications as it applies institutional theory to help understand the use of IT in government, as opposed to exploring the government as a regulator of the use of technology by other social actors. Another practical benefit of the TEF is identified by the researchers, who believe it may assist public managers to plan, design and implement e-government projects (Danziger 2004; Garson 2003b).

The framework has its drawbacks (Bretschneider, 2003; Norris, 2003), nonetheless it builds on the wider sociotechnical viewpoint (Luna-Reyes et al., 2005) and offers a valuable tool to gain insights into the complexities associated with technological use within the public sector. In addition to its influences with existing theory such as institutional theory, the TEF is also in line with, Orlikowski's notion of duality of technology (Orlikowski, 1992) and the wider social technical tradition, which acknowledges the interplay between the social, organisational aspects as well as material, technological dimensions (Galliers, 2006). As a result, it sheds light on the role public sector organisations (Luna-Reyes et al., 2005) play in shaping public sector technology use.

The enactment framework was originally developed to as a result of extensive research relating to the design and use of ICTs in government (Fountain 2005). The focus in this research for the enactment framework focuses purely on the use of technology, not the design elements. The framework can prove beneficial for the purposes of this study as it offers lenses to study how public

sector organisations, such as the NHS enacts technology according to their cultural, social and organisational features (Yildiz, 2007).

2.12 Conclusions

This chapter explored pertinent literature which sets the basis for this research. The extant literature acknowledges the need for human factors to be considered when exploring the use of BI. The literature review also explored the significance of power dynamics within both IS and healthcare literature. In doing so, it was identified that IS researchers have acknowledged the impact of IS on organisational power, yet no studies have explored the impact of BI in this regard. Furthermore, the literature review uncovered the role of IS in triggering power and conflict between healthcare professionals, mainly from a managerial and clinician perspective, therefore providing the basis to explore such dynamics from a management-analyst dyad.

As such, the chapter also focuses on decision-making literature and explores the rational decision-making models against more cognitive decision-making approaches. Accordingly, the literature review offers critical insights into the need for more research to explore BI decision-making from a non-rational disposition. Pertinent insights are also provided into the nature of decisions conducted across private sectors and public sectors, thus leading to environmental factors and more pertinently contextual factors pertaining to the case context of the NHS. In doing so, this chapter provides a critical overview of the importance of acknowledging environmental, as well as human behavioural factors when exploring decision-making, which is largely overlooked in discussions relating to BI decision-making. As such, these insights lead towards the focal chapter, in which the key constructs discussed in this chapter will be combined to formulate the conceptual framework for this research.

Shollo and Galliers (2016), employed an illustrative interpretive case study, using semi-structured interviews to gain deep insights into BI users and their interactions with BI systems. The study opened a new departure for BI

literature through the use of this methodology, thus proposing a conceptual framework of practises triggered by BI systems. There still however, remains a scarcity in existing studies investigating human factors during BI decision-making in the field of BI. Therefore, by also opting for an interpretative case study and placing greater emphasis on human behavioural factors, such as the role of intuition of individuals and other organisational actors from a differing context, the objectives of this research may be fulfilled and thus further explore the context and opening provided by Shollo and Galliers (2016). Therefore, the foundation for this study shall be in the form of an interpretive case study. This approach is ideal given the context of the question being explored in the study, particularly as studies are suitable for exploring 'how' related questions (George and Bennett 2005). This will assist in exploring how the various organisational actors operate, and how they ultimately interpret and internalise the intelligence from the BI systems. In depth semi-structured interviews involving open-ended questions will be utilised to uncover deep, cognitive aspects which are central to the context of the research. This study will also use observations to examine the interactions between various organisational actors when engaging with and following the use of BI tools and highlighted in more detail later.

The study at hand will primarily seek to explore the objectives stipulated in chapter 1 by placing the organisational actors at the forefront of the research. While literature extensively discusses technology and its processes, the study will examine its relationship with its users. As there remains limited discussions that address how BI analysts or decision makers interact with each other during BI decision-making. Therefore, it is befitting to examine whether during organisational actors' interactions with BI tools and applications, they are becoming more influential and superior in their disposition within the organisational setting. In order to aid this, Table 2.6 provides a classification of this chapter, decomposing relevant themes and elements of this study into BI dimensions and constructs. These constructs shall be used to aid the creation of an appropriate schema to address and explore the research objectives identified, during the data collection stages.

BI definitions	**Technology view**: Chaudhuir et al. 2011; Carvalho and Ferreira (2001); Burton et al., 2006; Hostmann and Rayner 2009; Kudyba and Hoptroff 2001, Scoggins 1999 , Hackathron 1999, Baars and Kemper 2008, Jermol et al. 2003; Nelson et al. 2005; Schultz 2004; Wang and Wang 2008; Dekkers et al. 2007; Negash 2004, Clark et al. 2007, Geiger et al. 2008; March and Hevner 2007; Watson 2009; Watson and Wixom 2007; Shariat and Hightowler 2007; Steiger 2010; Yermish et al. 2010 Chaudhuri et al. 2011, J. Ranjan 2005, Olszak and Ziemba 2006, Olszak and Ziemba 2007, Fowler 2000, Hajiheydari 2012; White 2004; **Process view of BI:** Wu et al., 2007; Burton and Hostmann 2005; Gartner 2010; Howson 2008; Imon and Nesavich 2008; Markarian et al. 2007; Okkonen et al; 2002; Sabherwal and Becerra-Fernandez 2011; Sigel and Shim 2000 **Multidimensional perspective of BI:** Brockmann et al., 2012; Ghazanfariet al., 2011; Golfarelli et al., 2004; Oyku et al. 2012; Alter 2004; Moss and Atre 2007; Isik et al. 2013; Jones 2010; Ponniah 2010; Popovic et al. 2010;

Data types.	**Structured and Unstructured data:** Baars and Kemper 2008; Mohammadi and Hajiheydari 2012; Negash 2004;Blumberg and Atre 2003; Rudin and Cressy 2003; Devlin et al. 2011; Dubey et al., 2015 Holsapple et al. 2014 SAS 2016; IBM 2017; M2 Presswire 2016; Sharma et al. 2014; Ashrafi et al. 2014; Clutch 2016; Rathinasamy 2015; Sukumaran and Sureka 2006; Isik et al. 2013
Data processing Tools	**Data mining:** Berry Michael and Linoff 1997; Kennedy et al. 1998; Dubey et al. 2016; Tan et al. 2005; Roiger and Geatz 2005; Fayyad et al. 1996; Shiraz Hashmi and Ahmad 2016; Liao et al. 2012; **Data warehousing:** Inmon 2005; Inmon et al., 1999; Kimball and Ross 2002; Stolba et al. 2006; Khan and Abu Sayed 2015; Sen and Sinha 2005; Devlin 2010; Eckerson 2003; Ariyachandra and Watson 2010 **OLAP:** Jarke et al. 2000; Turban et al. 1999; Golfarelli et al. 2012; Singhal and Jajodia 2006; González and Berbel 2014; Mansmann et al., 2014;
Intuition	Klein 1993, 2003; Dane and Pratt 2007; Kahneman and Klein 2009; Salas et al., 2010; Sadler-Smith 2010; Abernathy and Hamm; 1995; Stanovich and West 2000; Biggs and Wild 1985; Eggleton 1982; Gobet and Simon 1996; Neisser 1976; Simon and Chase 1973; Salas et al. 2010; Sadler-Smith 2010; Abernathy and Hamm, 1995; Klein, 2003; igerenzer and Wolfgang 2011

Sense making	Weick 1995; Gorelick and April 2004; Henfridsson 2000; Klein 1993; Klein et al. 2007; Weick, 1993; Hales 2007; Klein et al, 2006; Lycett 2013; Sorensen and Kakihara, 2002; Leonard and Sensiper 1998; Shollo and Galliers 2016; Lycett 2013
Types knowledge: Explicit / Tacit	Davenport and Prusak, 1998; Leonard-Barton and Sensiper,1998; Huysman and De Wit, 2002; . Polyani 1958, 1966; Khan and Quadri 2012; Herschel and Jones 2005; McKnight 2002; Shollo and Galliers 2016; Becerra-Fernandez and Sabherwal 2015; Altheide and Johnson, 1994; Kuhn and Jackson 2008;
Organisational Power dynamics	Gordon and Grant 2005; Heizmann et al. 2015; Hislop 2013; Kaerreman, 2010; Olsson, 2007; Rechberg and Syed 2013; Simeonova, 2017; Bradshaw-Camball and Murray, 1991; Foucault 1977; Doolin 2004; Barki and Hartwick, 1994; Beath, 1991; Dennis et al. 1998; Clegg et al., 2006; Kärreman, 2010; Lawrence et al., 2012). Bradshaw-Camball and Murray 1991; Sillince and Mouakket 1997; Fincham 1992; Thorelli, 1986; Crozier and Friedberg 1992; Ramsay 1994; McDonald, 1999; Cox 1999;Cooket al. 1983; Lee 1991; Kahkanen 2014; Essabbaret al. 2014; Davenport and Prusak, 1998; Leonard-Barton and Sensiper,1998; Huysman and De Wit, 2002; . Polyani 1958, 1966; Khan and Quadri 2012; Herschel and Jones 2005; McKnight 2002; Shollo and Galliers 2016; Becerra-Fernandez and Sabherwal 2015; Altheide and Johnson, 1994; Kuhn and Jackson 2008; Hardy 1996; Luke 1974; Azad and Faraj 2011; Kuhn and Jackson 2008; Hardy 1996; Luke 1974; Azad and Faraj 2011; Swan and Scarborough 2005;

Healthcare specific project challenges	Bick et al. 2014; Burnett et al. 2010; Craig et al. 2002;Evenstad, 2015;Tuffrey-Wijne et al. 2014; Exton 2010; Robertson et al. 2013; Trebble et al. 2013; Scholefield 2007; Williams et al. 2008; Wright and McSherry 2013;Simms et al. 2014; Tuffrey-Wijne et al. 2014; Ross et al. 2014; Berkeley and Springett 2006; Frame et al. 2008; Ross et al. 2014; Brooks 1996; Ramsay et al. 2014; Kristensen et al. 2013; McDonald 2005; Millar 2013; Spilsbury et al. 2011; Walshe et al. 2001; Cowley et al. 2002; Davies et al. 2011; Craig et al. 2002; Goldie and Sheffield 2001; Rivas et al. 2010; Larsen et al. 2013; Lord et al. 2014
Healthcare specific human factors	Russ et al. 2014; Brewster et al. 2013; Williams et al. 2008; Lawton and Parker 2002; Fear et al. 2003; McDonald 2005; Curnock et al. 2012; Simms et al. 2014; Shaw and Siriwardena 2014; Twycross 2013; Bloe et al. 2009; Hewison et al. 2014 Maden-Jenkins 2011; Taylor et al. 2014; McNaughton et al. 2011; Mowles et al. 2010; Williams et al. 2008; Ramsay et al. 2014; deodu et al. 2009; Slater et al. 2012; Robertson et al. 2013; Pagliari et al. 2012; Checkland et al. 2007;
General decision-making human factors	Borghans et al. 2008; Cowan 2010; Newell and Simon 1972; Mellers, Schwartz, & Ritov, 1999; Shah et al. 2012; Manyika et al. 2011; Chen et al. 2012; Masaros et al. 2016; Miller 2014; McAfee and Brynjolfsson 2012; Yang 2011; Almlund et al. 2011; Filiz and Battaglio 2017; Costa and McCrae 1988; Borghans et al. 2008; Hogan et al., 1996; Klein et al. 1993; Dane and Pratt 2007; Langley et al. 1995; Bazerman and Moore 2008; Blackler and Popovic, 2015; Fischer et al. 2015; Berlyne 1954, 1966, 1978; Engel 2011; Gottlieb et al. 2013; Hebb 1955; Kang et al. 2009; Piaget 1969; Loewenstein 1994

Table 2.6: Study classification

3.0 CHAPTER 3: Developing a conceptual model: '*BI Power Enactment Framework'*

3.1 Introduction

The review of the literature in chapter 2 establishes that BI literature has largely been investigated from its technical and architectural contexts, whilst overlooking human factors associated with BI use. Nonetheless, BI as an area of academic research is transitioning, treading a new path, as reflected through the human-centric approach recently taken by Shollo and Galliers (2016) in exploring the role of BI tools in knowledge creation. Nonetheless, more studies are required to understand the use of BI within organisations, through the lenses of various organisational actors. As such, the focus of this study is to further explore BI from a human centric perspective. The movement away from the technical aspects relating to BI and emphasis of human aspects in BI research is an emerging field of academic literature, presenting many research opportunities. As such, this chapter aims to develop a conceptual framework which will assist in exploring the role of BI in impacting power dynamics within the case context.

The rationale for this research are many, firstly it is widely accepted that BI use within healthcare is both promising and necessary, particularly given the enormous amounts of data collected by healthcare organisations (Chen et al., 2012, El-Gayar and Timsina, 2014, Fichman et al., 2011; Gastaldi, et al., 2018) and its role through BI use in enhancing patient care (Tremblay et al., 2012), improving human resource utilisation (Crist-Grundman & Mulrooney, 2011), reducing costs (Pine et al., 2012) and offering greater efficiency of processes (Flower 2006). While, Lucas (2004) argues that the huge amounts of data collected by healthcare organisations, such as NHS is treasure for data analysts, there is little understanding of how BI is being used within the healthcare sector, more so how the analysts are utilising the data for decision-making purposes. The reasons for this are manifold, while acknowledging BI

research within in healthcare (Foshay and Kuziemsky 2014; Brook et al., 2015; Tremblay et al., 2012) the focus has preliminary been on the intended outcomes of using BI (i.e. improved decision making) or tools for supporting BI. However little studies to date have explored how BI use used by various organisational actors within the healthcare context, and there have been little insights into how the use of BI is impacting the power dynamics within healthcare services, particularly given the interdependent and interconnected nature of healthcare operations. Therefore, in line with the human centric motivation of this research, the study will establish how various organisational actors use BI with the aim of exploring the impact it has on power dynamic relationships in the NHS. The NHS digital challenge, whereby the organisation is committed to going paperless by 2020 is another motivation for this research. Therefore, exploring how BI is currently being used and by identifying key insights into power considerations resulting from its use, not only offers practical implications for the organisation, but is also a timely and highly relevant area of research within the healthcare sector in the UK.

Focusing in on the central premise of this research, it is argued that prior research has highlighted that healthcare processes, namely decision-making are not isolated events, rather, are a combination of interrelated, reciprocal actions between processes people and technology (Foshay and Kuziemsky, 2014; Thraen et al., 2012). Yet, the focus of existing BI research has been on either the former or the latter, omitting and overlooking the people element and its associated synergies with both the technology and the processes. As such, this research aims at overcoming this void, by evaluating how the organisational actors (people) utilise BI (technology) during the decision-making process (processes). Furthermore, Brooks et al. (2015) argues that in order to accomplish a successful BI strategy, it is imperative to understand how organisational actors think and work with one another. As such, by paying attention to organisational actors such as the functional managers, which include operational managers, service managers, business managers and the data analysts, will assist in offering insights into intra-organisational dynamics, thus enhancing the overall understanding of this.

3.2 Theory use in IS studies

The use of theory in research has attracted much attention. Eisenhardt (1989) outlines three approaches to theory use in organisational research; as an initial guide to design and data collection; as a component of an iterative process of data collection and analysis; and as a final product of the research. While Eisenhardt (1989) takes a positivist position, these various approaches she endorses have also been applied in interpretivist IS research. For instance, theory used to initially guide design and data collection has been implemented by Walsham (1993) who draws on the theory of contextualism by Pettigrew (1987, 1990) to inform the basis of his interpretive study on IS strategy, Walsham and Sahay (1999) also use the Actor Network Theory to analyse GIS implementation in India. Furthermore, theory can also be used as part of an iterative process of data collection and analysis as done so by Orlikowski (1993) whereby she uses data derived by grounded theory in conjunction with 'existing formal theory' from innovation literature (regarding the distinction between incremental and radical types) or as the final product of a research as done by Orlikowski and Robey (1991) who draw upon their own work as well as Giddens (1984) structuration theory to construct a final product in the form of a theory. Therefore, the researcher supports the use of theory and upholds Walsham's (1995:77) view that 'it is possible to access existing knowledge of theory in a particular subject domain without being trapped in the view that it represents final truth in that area'.

The use of theories during the initial stages of interpretive cases studies assists in building a theoretical framework that acknowledges previous knowledge, and therefore generates a sensible theoretical premise to guide the topics and approach of empirical work, early on (Walsham 1995). Hence, this research will also draw upon various relevant strands of theory that will guide the approach to the data collection. While Alvesson (1996) endorses the use of one key theory, Walsham (1993) on the contrary recommends the use of multiple theories, arguing that the theoretical literature principally serves as a source for inspiration and is used to contribute in the understanding of

complex social situations. Thus, in accordance with the latter, the theoretical dimensions from existing literature will aid in guiding the data collection.

3.3 Conceptual framework development

The research will adapt and combine existing theories and key literature to guide this research and act as a sense-making, analytical tool. Combining theories in order to gain a better understanding of the use of IS well evidenced from within the extant literature (Gibbs o Kraemer, 2004; Hsu, Kraemer, o Dunkle, 2006; Oliveira o Martins, 2011; Mahroof 2019; Zhou, Lu, o Wang, 2010). Although these theories are more specifically used to explore IT adoption, many of the cases are broadly interrelated to IS use. More specifically, Chan et al., (2011) adapt the Resource-based view (Barney 2001) and the Enactment Concept (Orlikowski 2000; Weick et al., 2005) as a theoretical sense-making lens to explore e-Government system implementation. Similarly, Tassabehji et al., (2016) also take a similar approach by incorporating additional dimensions, which in this particular research was relating to e-Government policy and the role of the Chief Information Officers (CIO), to TEF (Fountain 2005).

Accordingly, to facilitate this research and assist in addressing the research question, this research aims to incorporate theoretical constructs 'Organisational Dimensions of Power' (Hardy 1996), Enactment of technologies-in-practice (Orlikowski 2000), along with literature relating to human behavioural factors and environmental factors (Lizarraga et al. 2009). Lukes (1974) seminal work and original conception of the multidimensional nature of power has provided much of the impetus and motivation for Hardy (1996) to explore power dynamics within organisations to achieve strategic change. The theory is founded on three fundamental sources of power, resource power, process power and meaning power.

As this research is concerned with the role of BI in impacting the power dynamics within the NHS, an organisation that is driving for strategic change through its digital transformation and paperless agenda, by acknowledging

these sources of power, will assist in taking a multi-modal approach in exploring the dyadic relationship between power dynamics and IS within organisations. The Enactment of technologies-in-practice (Orlikowski 2000) refers to three types of enactment which organisational actors may opt for, namely *Inertia, Application and Change* enactments. Inertia refers to when organisational actors have limited-use technology in-practice and choose to use technology to retain their existing way of doing things with limited change to the way in which the technology is enacted. The application enactment refers to when actors use the technology to augment or enhance their existing ways of doing things, as such the technology is used with the motivation to enhance existing work processes. The final type of enactment proposed can be characterised by change, whereby organisational actors use technology to substantially alter their existing way of doing things. Accordingly, the change enactment largely related to the improvisation technology-in-practice, whereby users decide to adapt or customise aspects of their tools and its data content to refine work or achieve new ways of working. The key works on technology enactment (Fountain 2000; Weick 1979; Orlikowski 2000) considers contextual factors which may influence the types of enactments which occur. Accordingly, environmental factors which in the context of this research, are specific to the healthcare will be a key feature in the proposed framework. The human behavioural factors will also be included in the framework, thus through incorporating factors such as cognition (Borghans et al. 2008), personality (Filiz and Battaglio 2017), intuition (Blackler and Popovic 2015), curiosity (Harvey et al. 2007), will offer insights into human factors, which are largely overlooked in BI studies. Accordingly, the key theoretical constructs for this research are highlights in Table 3.1.

Dimension / Construct	Definition	Source
Organisational Power source: Resource	This dimension of power refers to the ownership of resources. Organisational actors who possess some type of resources are more likely to coerce others into behaving according to their will. Examples of resources include; “information, expertise, political access, credibility, stature and prestige, access to higher echelon members, the control of money, rewards and sanctions	Hardy 1996
Organisational Power source: Process	Power is also attributed to the decision-making process, and refers to people who have domination over such processes are entitled to coerce others by applying or not applying “procedures and political routines”	Hardy 1996
Organisational Power source: Meaning	Meaning power relates to the power to prevent “conflict from emerging in the first place” (Hardy, 1996, p. S8). That is, some people have control over the status quo, and by doing have the ability to overwhelm others from their cognition	Hardy 1996

Enactment of Technology in Practice	Enactment enables a deeper understanding of the emergent, unprecedented, and innovative ways in which people engage with new technology in organizations and over time	Orlikowski 2000
Human cognitive Factors: Cognition	The mental action or process of acquiring knowledge and understanding through thought, experience, and the senses.	Borghans et al. 2008; Cowan 2010; Newell and Simon 1972; Mellers, Schwartz, & Ritov, 1999
Actor skillsets	Skill-set of actors according to their role and responsibilities, in context of this research refers to analytical, technical skills.	Shah et al. 2012; Manyika et al. 2011; Chen et al. 2012; Masaros et al. 2016; Miller 2014; McAfee and Brynjolfsson 2012;
Personalities	The patterns of thought, feelings, and behaviour and in line with their understanding, through focusing on individual differences in how organisational actors actually think, feel, and act, not on how people want to think, feel, and act	Yang 2011; Almlund et al. 2011; Filiz and Battaglio 2017; Costa and McCrae 1988; Borghans et al. 2008; Hogan et al., 1996;

Intuition	This can be described as an automated processing style which allows decision makers to rapidly process large quantities of information, without consciously acknowledging the occurrence of this process	Klein et al. 1993; Dane and Pratt 2007; Langley et al. 1995; Bazerman and Moore 2008; Blackler and Popovic, 2015; Fischer et al. 2015
Curiosity	it is argued that curiosity can be understood as the ambition of reducing information gaps, which effectively is the difference between '*what one knows and what one wants to know';*	Berlyne 1960, 1966; Engel 2011; Gottlieb et al. 2013; Hebb 1955; Kang et al. 2009; Piaget 1969; Loewenstein 1994
Target pressures		Robertson et al. 2013; Adeodu et al. 2012; Slater et al. 2009;
Silo mentality	Conflicting priorities	Lord et al, 2014; Craig et al. 2002; Larsen et al. 2013; Whitelaw et al. 2012; McQuillan et al. 2014

Culture	due to NHS policy-makers and operational, clinical staff holding conflicting sentiments, attitudes and interests dominant disciplinary divide of roles and the tribalism within the NHS	Elwyn et al. 2012; Brooks and Brown 2002; Bunniss et al. 2012
Fragmentation	Lack of information sharing and shared ways of working	Kristensen et al. (2013)
BI triggered practices: Data selection by decision maker	'Drill down' and 'roll up' activities users perform via BI systems provides transparency and visibility. Data at various levels, time dimension and data quality strengthens the case of data being evidence	Shollo and Galliers (2016)
Variations of Articulation practices	Interpretation by analysts of new distinctions from BI data that requires further investigation. Process of various organisational actors articulating, contesting and negotiating the new dimensions, in order to make sense of the new distinctions	Shollo and Galliers (2016)

Table 3.1: Conceptual framework construct

According to Hardy (1966), the first dimension of power stems from the possession of resource, whereby organisational actors who possess particular resources are considered more likely and successful in coercing other organisational actors to conform in accordance to their wishes. These significant resources can be in form of information, expertise, political access,

credibility, stature and prestige, access to higher echelon members, the control of money, rewards and sanctions" (Hardy, 1996: S7). In the context of the NHS, this resource can refer to any of the above, particularly given the politically nuanced nature of the organisation. However, for the purposes of this research, this resource dimension of power will be used to explore the BI expertise and the analytical skill-set which certain organisational actors possess.

In addition, the process power refers to the power which emanates from the decision-making process, thus certain organisational actors who have control over this process are able to coerce organisational actors through their ability to either regulate or omit this "procedures and political routines" (Hardy, 1996:S7). As such, this would to not only senior management, but also the functional managers operate within the wards and services, have the ability make decisions, enforce procedures and policies. The final dimension of meaning power refers to the ability of dominant actors to prevent conflict occurring in the first place, through attempting to alter views and norms through the control of shared meaning among a group of social actors by another group of actors. This source of power therefore is seen as operating the semantic facets of organisational life, involving the legitimation or de-legitimation of certain activities (Swan and Scarborough 2005). For the purposes of this research, this can help explore some of the more subtle, yet political influences that are prevalent as a result of the data-driven culture of the organisation.

Consequently, in order for these dimensions of power to be explored more precisely, the context in how these are being exercised also requires examining. Therefore, the conceptual framework for this research also theoretically relies on the 'Enactment of Technology in Practice ' (Orlikwoski 2000), as lens to understand better the relationship between various groups of actors and BI use, through exploring how it is used by various organisational actors. Expanding this further, Orlikowski (2000) refers to the virtual technology structures which emanates through the repeated and situated interplay between organisational actors and certain technologies. The term

‘technologies-in-practice’ refers to the institutionalised process of similar technology-use between a community of users, which becomes firm prescriptions for social action that may either impede change or reinforcement (Orlikowski, 2000). As such the ‘Enactment Technology-in-Practice’ is pertinent to guide this research, as it not only brings a structuration dimension and perspective that acknowledges technology use, which in this case is BI technology, it also differs to previous Structurational models, such as ‘The Structuration Model of Technology’ (Orlikowski 1991). This model outlines that technology can impact an organisation through the appropriation of organisational actors, although it is a medium of human action. This is achieved through constraining and enabling, hence conditioning social practices. However, for the purposes of this research.

Therefore, given the human-centric focus of this research, rather than beginning with the technology and investigating how actors appropriate its embodied structures, the ‘Enactment Technology-in-Practice’ starts with human action and examines how it enacts emergent structures through recurrent interaction with the technology at hand (Orlikwoski 2000:407). Accordingly, this is ideal for the purposes of this study, particularly given its human-centric emphasis in exploring various organisational actors and their use of BI. Therefore, by incorporating ‘Enactment Technology-in-Practice’ aspects into the conceptual framework for this research will help tease out whether the way in which the BI is used has implications on the power dynamics, through the three dimensions of power (Hardy 1996) within the NHS.

Orlikowski (2000) states that when organisational of actors within a community engage in similar work practices, they typically enact similar technologies-in-practice, as a result of undergoing similar training, sharing values and ethos, through their similar on-the-job experiences, and with shared direction and storytelling, thus organisational actors begin to engage with a technology in an analogous manner. However, through recurrent reinforcement by the actors within a community, such technologies-in-practice may reify and institutionalize, as a result of which, they manifest and become considered as

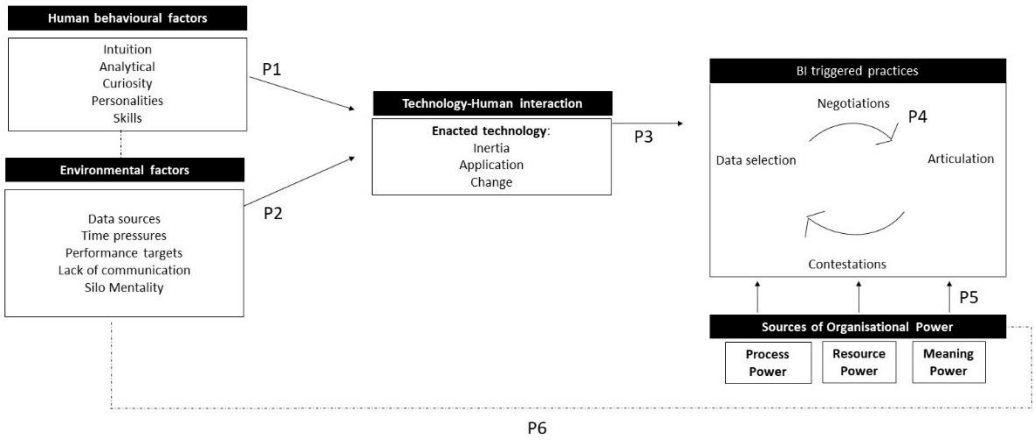
fixed prescriptions for social action. Therefore, through the use of 'Enactment Technology in practice', this research will examine the extent of regularised engagement of functional managers and the data analysts with BI, thus exploring whether and how organisational actors from these groups repeatedly enact a set of rules and resources which structures their ongoing interactions with the BI technology. As such, the conceptual framework for this research is depicted in Figure 3.1.

The implications of contextual factors, such as time-related strains with specific organisational, work-related, and personal conditions of workers has previously received much attention (e.g., Vagg & Spielberger, 1998; Carayon & Zijlstra, 1999; Teuchmann, Totterdell, & Parker, 1999; Major, Klein, & Ehrhart, 2002) however, the role of cognitive, human factors, has not received much empirical attention particularly from within a BI decision-making context. Therefore, factors such as the relevance of curiosity from a decision-making context is further explored by Baharlou (2017), who develops a model of choice with curiosity using Loewenstein's interpretation of curiosity. Therefore, accordingly, this research also incorporates such behavioural factors to understand how BI is used as a result of such cognitions, whilst examining how this may impact power considerations between organisational actors.

3.4 Justifications for the proposed conceptual framework

The key dimensions which form the conceptual underpinning of this research are purposely selected and can be justified in a number of ways. The organisational dimensions of power (Hardy 1996) have specifically been chosen for this research as they have previously been used when exploring strategic change within organisations. Given that the NHS is undergoing a digital transformation and the use of BI as part of a wider strategic change initiated by the organisation, these dimensions of power were deemed suitable. Furthermore, the choice to opt for TEF, and more specifically the 'Enactment Technology-in-Practice' (Orlikwoski 2000) is due to this framework

widely being recognised as valuable when exploring the influence of organisational structures and institutional arrangements of technology use within the public sector (West, 2004; Yildiz, 2007). Majority of studies which utilise the TEF are largely conducted in public sector organisations (Antonio Cordella and Iannacci 2010; Hassan and Gil-Garcia 2008), as also is the case in this research. Furthermore, the critical difference between 'Enactment Technology-in-Practice' and other models such as The Structuration Model of Technology' (Orlikowski 1991), is that the former begins with human action and examines how actors may enacts interactions with the technology at hand (Orlikwoski 2000) for particular reasons, as opposed to the other way, i.e. the impact of technology on the actors. Thus, this perspective given the human-centric focus of this research is ideal. Moreover, existing BI studies can be criticised for not considering cognitive, behavioural factors which may determine the way in which decisions are reached. As such, this research



focuses to overcome this by considering such factors which are central to the proposed framework. Furthermore, and in-line with technology enactment methodology, contextual factors based on empirical studies conducted within healthcare will also be incorporated in order to provide the contextual factors which may also play a part in BI decision-making.

Figure 3.1: Power Enactment Conceptual Framework

The background theory has outlined how the extant literature is heavily geared towards organisational BI performance, BI success factors, and architectural aspects of BI, whilst overlooking the human elements. Accordingly, this research aims at exploring the role of BI in impacting power dynamics within the NHS through proposing a sense-making conceptual framework, that acknowledges originating sources of power, such as resource, meaning and process power as well as exploring human agency, through the enactment dimension, which conveys the sense of 'to constitute, actuate, perform' (Orlikowski 2000: 425) concept. This framework will assist in exploring how various organisational actors use BI and how this use, impacts the dynamics of power and influence within the NHS trusts. As depicted in Figure 3.1, the conceptual framework also reflects key areas of BI literature, by acknowledging recent insights into the articulation and potential contestations which occur during BI decision-making processes. The extant healthcare studies can be critiqued in their assumption that decision making processes are in place to support the effective use of BI systems in the healthcare sector. While BI is a growing trend and increasingly becoming a notable interest within healthcare, its implementation and adoption, despite all its potential, is not widespread in healthcare (Hanson, 2011)

Shollo and Galliers (2016) highlight how BI impacts knowledge work in organisations, through the practises of data selection and articulation. However, the organisational actors professionalism, skillset and experiences are deemed as essential requirements for such practises. The interlinking BI nature of data, technical tools and sensemaking is apparent from the study of Shollo and Galliers (2016). However, their contribution to how knowledge is created via BI systems through practises of 'data selection and articulation' resonates with Lycett's (2013) earlier understanding of 'datafication'. Lycett (2013) outlines that BI and analytics enables decision makers and managers to connect IT and sense-making together into a process of datafication that allows them to exploit data and analysis in order to recognise the phenomena that is rooted in the data. Lycett (2013), similar to Shollo and Galliers (2016) argues that regardless of the data driven disposition of IT sense making,

cognitive sense making also occurs, be it sub-consciously through pre-existing frames of references held by managers and analysts.

These cognitive influences play a role in deciding which data elements are chosen to describe a given phenomenon, whilst also influencing what trends and relationships connected to the data elements are deduced. These insights are thereby applied by the analysts and managers to entwine an account making sense of the world, which lead to actions that bring the interpretations to light explicitly. Although Shollo and Galliers (2016) display the cognitive workings of decision makers in their study, the capabilities of BI tools are continually advancing and over time and as contexts changes, different structures can also emerge, which can also lead to the potential for innovation and learning (Orlikowski, 2000). An appreciation of the 'Individualist' and 'Social' BI paradigms are important, particularly given that enactment is closely associated with the contextual environment (Weick, 1979, 2001), whereby actors operate in accordance to their various environmental stimuli (Fountain, 2001; Daneels, 2003). Therefore, addressing the contextual environments in which BI is interacted with by the organisational actors is ideal.

3.5 Research Propositions

Accordingly, based on the existing literature and drawing upon the research questions, this study presents the following research propositions which will assist in exploring how BI use impacts power dynamics within the NHS context:

Proposition 1: Human behavioural factors influence the way in which BI is enacted and used by organisational actors

Proposition 2: Environmental factors influence the way in which BI is enacted and used by various organisational actors

Proposition 3: The way in which BI is enacted by organisational actors impacts BI articulation and the BI decision-making process

Proposition 4: Data articulation occurs between various organsational actors during BI decision-making

Proposition 5: The use and BI technology enactment by organisational actors within the NHS is bringing about a shift in power dynamics through 'Resource, Meaning and/or Process' power dimensions.

Proposition 6: Environmental and behaviour factors also has an indirect impact on power dynamics between various actors

The proposed theoretical framework for this research has a twofold purpose. Firstly, it aims at establishing how BI is being used within the organisation, between various organisational actors. Secondly this framework aims to assess the impact of such use on the power dynamics between these users. Accordingly, these research propositions concerns how BI is used and what impact it has on power dynamics within the NHS trust. The key themes deduced from the background theory, which are also categorised in Table 2.7 will act as an interview guide, in conjunction with the sense-making conceptual framework to further explore these research propositions, in order to help gain a more knowledgeable insight into the role of power dynamics within the NHS, through its utilisation of BI tools.

3.6 Conclusions

This chapter develops a conceptual framework which is underpinned by the academic literature reviewed in chapter 2. As such, the chapter brings together pertinent areas of the literature as well as key theories, in order to explore how BI is used by organisational actors, and its impact on organisational power dynamics. Based on the literature review, the conceptual framework

specifically identifies human behavioural factors along with environmental factors as key decision-making influences. The conceptual framework has a twofold purpose, firstly by extracting these dimensions from the literature, the conceptual framework looks to explore how these factors impact the way in which BI is enacted by organisational actors through the lenses of the Enactment Theory. The purpose for this, as established through the literature review, is that the extant BI literature takes a rational disposition when considering the process of BI decision-making. There is the assumption that data is transformed into actionable information and thus leads to decision-making, without taking into consideration factors which may impact how the BI may be used in the first instance. Therefore, by combining decision-making literature with The Enactment Theory will provide valuable insights into BI decision-making from a human perspective.

Secondly, the framework examines how decisions are reached between various organisational actors, during BI articulation. Whilst Shollo and Galliers (2016) acknowledge that iterative and dynamic processes associated with BI decision-making, by referring to the articulation of BI generated data between actors, the authors overlook how power considerations may impact such interactions between the actors. As a consequence of this, the conceptual framework explores the BI articulation between various actors through the theoretical constructs of Process, Resource, Meaning sources of power (Hardy 1996). This particular theory was used as opposed to others, to examine the power dynamics, as Hardy (1996) sources of power is commonly used when exploring an organisation that is going through a strategic change, as is also the case for the NHS and their ongoing digitisation plan.

4.0 CHAPTER 4: Methodology Chapter

4.1 Introduction

This research aims to explore and gain an insight into the relationship between BI systems and their users during organisational decision making. The nature

of this relationship is complex and deep-rooted, therefore in investigating this phenomenon the research design of this study requires meticulous attention. This chapter discusses philosophical positions in social sciences and then outlines the chosen philosophical position for this research. This research is underpinned, influenced and supported by this philosophical position which accounts for both ontological and epistemological stances, as will be outlined in the following section. Furthermore, this chapter is concerned with presenting justifications for the proposed research design and strategy of this study.

4.2 Philosophical research paradigm

Philosophy is a fundamental element of research which helps to inform the approach a research could take in examining the phenomenon by determining their view of the world (ontology) alongside the methods to understand the nature of knowledge (epistemology) (Van de Van 2007). An array of sociological paradigms have been forwarded by various authors, for instance Burrell and Morgan (1979) propose interpretive, functionalist, radical structuralist, and, radical humanist; Guba and Lincoln (2000) Define Positivism, Post Positivism, Constructivism, Participatory Paradigm and Critical Theory; and, Van de Van (2007) highlight Positivism, Relativism, Pragmatism and Realism. However, within the field of IS, Positivism, Interpretivism and Critical Perspectives are commonly endorsed (Orlikowski and Baroudi 1991; Walsham 1995, Myers 1997; Oates 2006, Ponelis 2015). Various aspects need to be taken into consideration when adopting a philosophical position for a study, such as the research topic, access to research and the chosen theory. Furthermore, the appropriateness of a philosophical perspective also relies on the research objectives of a study.

4.2.1 Ontology

Ontology refers to the study of being, referring to the fundamental nature of the world, concerning ‘what is’ with the nature of existence (Crotty 1998). Thus, ontologically the reality can be understood free of the observer, in an objective

manner (Saunders et al. 2009) or on the contrary, reality can be viewed subjectively, created from the perceptions and actions of social actors (Bryma2012). The objectivist assumptions view reality as a concrete given that imposes upon and even determines individual behaviour. From this problematic, knowledge is perceived as real in the arrangement of recognisable, quantifiable, laws and patterns (Cunliffe 2011). Objectivism focuses on structures, actions, systems and processes. However, the researcher will take the subjective position, upholding the view that social phenomena and their meanings are continually being accomplished by social actors (Bryman 2012). The subjective view is ideal, as this research concerns organisational actors and their understanding and interpretations of BI, therefore aiding the deep, personal insights required to fulfil the research objectives.

4.2.2 Epistemology

Epistemology concerns the status of knowledge, entailing 'how we know, what we know', focusing on how the knowledge is acquired, and what constitutes the basis of our knowledge (Hallebone and Priest 2009). Maynard (1994: 10) posits, 'Epistemology is concerned with providing a philosophical grounding for deciding what kinds of knowledge are possible and how we can ensure that they are both adequate and legitimate'. Therefore, identifying, explaining and justifying the epistemological position for a study is vital at the offset. One could take a positivist or an anti-positivist/interpretivist position in undertaking research. The epistemological position chosen for this research is interpretivism, as opposed to positivism. According to Trauth and Jessup (2000), the interpretivist paradigm places emphasis on the intricacy of human sense making, as the situation unfolds. Interpretivism is appropriate for this research as it is mainly concerned with the study of human interaction with the BI phenomenon. Interpretivist ontology perceives reality and knowledge as social products that are not independent of the social actors, thus it views the world as being produced and reinforced through interaction and action by

humans, as an extension of human consciousness and subjective experience (Burrell and Morgan 1979: 253). The research therefore fits this, as it does not aim to test hypotheses, rather aims to explore intuitiveness and effectiveness of BI users. However, the positivism perspective is also an underlying research paradigm underpinning IS research. Therefore, in order to justify the philosophical position for this study, these dichotomous approaches will be discussed.

4.2.3. Positivism

The Positivism/Interpretivism debate has long been contested between various scholars in the field of IS, some have approached the discussion in a reconciliatory manner, proposing integrated views (Fitzgerald and Howcroft 1998; Weber 2004) while others have insisted on their detachment and incompatibility (Orlikowski and Baroudi 1991; Walsham; 1993, 1995). Positivist philosophy adheres to the principles that only external, 'factual' knowledge that is confirmed by senses, i.e. through observable phenomena, or measurement can be warranted as trustworthy knowledge (Hughes and Sharrock, 1997). Positivists hold the view that reality is objectively set and can be described by measurable properties, which are independent of the observer (researcher) and his or her instruments (Myers, 1997). Remenyi et al. (2000) explains positivism philosophy as law-like generalisations similar to those in the physical and natural sciences.

This form of research is conducted in such a manner that is objective, therefore having implications for the researcher, whose role may be limited to only collecting and objectively interpreting the data, in a value free manner. As a result quantitative research generally offers no provisions for human interests in a study. Burrell and Morgan (1979) highlight that positivism focuses identifying and explaining casual relationships between concrete constructs, thus providing the foundations for generalisations and explanations of laws to be assessed (Bryman 2012). However, the methods derived from the positivism approach runs the risk of being too rigid and artificial, particularly

when a phenomenon requires deeper, richer attention to detail (Saunders et al., 2009). As a result, for this research, such potential limitations can curb the prospect of yielding in-depth, deeper understanding of how the users gain tacit knowledge, and increase their personal intuition as a result of using BI tools.

While research in the field of IS has been endorsed from a positivist position (Keil 1995; Pare and Elam 1997; Markus 1983; Sambamurthy and Zmud 1999), it has also been challenged. For instance, Lee (1999) refutes Benbasat and Zmud (1999) endorsement of a positivist orientation for IS research by outlining that the over-arching positivist orientation has negatively plagued the essence of IS research, whilst overlooking alternative approaches. Lee (1999) posits that interpretive studies are necessary in order to progress a deeper, rich understanding of professional practise. Lee (2004) contests that researchers are required to not only observe IS from its technical orientation, but rather they must also consider exploring social elements and their continuing interaction, with regards to the use of IS and other technical developments in organizations. Supporting this call by Lee (2004), it can be disputed that in order to capture such social aspects, that studies with an underlying interpretive approach is suited.

4.2.4 Interpretivism

The alternative position to positivism is the ‘anti-positivist’ stance of interpretivism, which searches for ‘culturally derived and historically situated interpretations of the social life-world’ (Crotty 1998: 67). The central premise of interpretivism is understanding, as opposed to predicting, therefore dependent and independent variables are not predefined, rather focus is placed on the full complexity of human sense making as the situation emerges (Kaplan and Maxwell, 1994). Interpretivism is concerns revealing the inner most beliefs and values of a subject requiring a subjective focus and attention. A researcher can infer, observe and question their subjects in order to make sense of the social constructs, such as language, consciousness and shared

meanings (Myers, 1997). Interpretive studies generally attempt to understand phenomena through the meanings that people assign to them. Interpretivism shares the view that the social reality, i.e, people and institutions are fundamentally different than natural sciences, therefore the study of social world requires methods that echoes distinctiveness of humans (Bryman 2012), dealing with the individual actions as opposed to scanning for consistencies in the data with the aim of deducing 'laws' (Gray 2004).

Therefore, the role of the interprevist researcher is crucial in understanding and interpreting the meanings which people attribute to the phenomena in question, which includes understand contextual dynamics (Walsham, 1993; McNabb, 2004). As a result, adopting an interpretivism approach offers the opportunity to explore these deeper, untended elements in an in-depth manner, providing a rich, thick description. According to Bygrave (1989), the interpretive qualitative approach allows a study to generate a rich understanding of major issues by reducing the distance between the researcher and important organisational actors such as key decision makers, and managers. This can help develop both practise- based and theoretical insights, whilst potentially producing fresh, alternative concepts and theoretical dispositions that were previously concealed. Thus, offering an insight into the degree of intuition BI use generates in its users, as well as presenting an understanding of the degree to which multidimensions of power play a role during the practises of articulation between the plethora of actors in organisations.

Given the nature of this research, it was imperative to capture detailed insights into intricate relationships of organisational actors, particularly as Crotty (1998) argues that depending on the context quantitative research can fail to uncover the 'whole story'. Thus further supporting the philosophical stance for this research, which in congruence with past IS studies that have followed this tradition of research (Markus, 1983; Suchman, 1987; Zuboff, 1988; Boland and Day, 1989; Orlikowski, 1991; Walsham, 1993, 1995; Orlikowski and Robey 1991, Jones and Nandhakumar 1993; 2002; Walsham and Waema

1994; Suchman 1987; Walsham 1993; 1995; 2005; Fink and Disterer, 2006; Hill and Scott, 2004; Ponelis 2015, Shollo and Galliers 2016).However, despite taking an interpretivist approach, this research utilises a conceptual framework and existing theory, which is in line with the recommendations of Walsham (1995), who highlights the appropriateness of applying previous knowledge as 'scaffolding' in an interpretive study.

Walsham (1995) further posits argues the need for more interpretive research in the field of IS, as human interpretations regarding information systems are the central focus of IS research. This research therefore attempts to progress in this direction, though Walsham's (1995) remarks stem from several decades ago, he reinforces his sentiments when highlighting that *'Interpretive research has clearly become much more important in the IS field than it was in the early 1990s'* (Walsham 2005; 320). Furthermore, the nature of IS is such, it is continually progressive, therefore, the human interpretations will continue to uncover newer, untended elements, as a result requiring interpretative attention.

4.3 Research Method

There are different types of research strategies that can determine the choice of research methodologies for conducting research in social sciences (Fuchs and Hanning, 2001). The quantitative orientation is strongly linked to the Positivist epistemological approach discussed earlier. This form of research is typically concerned with answering questions such as 'how many?', 'what are the causes?' and 'what is the strength of a relationship between variables? Therefore, quantitative research excels in identifying statistically significant relationships between variables, and explains associations by establishing relative influences of individual variables for sub samples of populations (Barbour 2014). The approach therefore of the natural sciences is to observe consistencies in the data for the purpose to deduce laws, also referred to as a nomothetic approach to research.

On the contrary, the Qualitative approach is closely linked to anti-positivism in its nature, and answers very different questions to its dichotomous opposite.

It is defined as *'any kind of research that produces findings not arrived at by means of statistical procedures or other means of quantification*' (McLeod 1994: 77). This form of inquiry concerns yielding rich data about real life situations and people and is generally seen as being more suitable of sensing behaviour in order to understand it from its wider context, thus providing a fuller picture (De vaus 2002). Therefore the approach of social sciences towards research is mainly associated to the actions of individuals, thus referred to as an ideographic approach (Gray 2004).

In summation to the discussions raised regarding both dichotomous approaches, the appropriateness of the either approach depends on the nature of the research problem along with the type of information that is required to address the research questions. With this said, the qualitative approach combined with its associated philosophical assumptions is ideal for the research at hand, as it focuses on the social characteristics of life and the significance people ascribe to it (Creswell 2013).

4.3.1 Justification of the use of Qualitative research methods

The research orientation for this study is qualitative, and this section aims to provide justifications for this choice. Research approaches are subject to the underlying philosophical positioning of the researcher (Goldkuhl 2012), accordingly, the qualitative approach is compatible with the philosophical underpinning of the researcher, of a subjectivist ontology and interpretivist epistemology. The terms 'qualitative' and 'interpretivism' do not hold synonymic values (Myers and Avison 2005), as qualitative studies can also be performed alongside a positivist stance (Rezgui and Miles 2010), yet the lens most commonly influencing the choice of qualitative methods is interpretivism (Trauth 2001), thus supporting the qualitative approach for this research.

While the Quantitative research approach is well equipped at answering the where, what, who and when type of questions (Crabtree and Miller, 1999), it

fails to adequately answer why or how a phenomenon happens (Denzin and Lincoln 2000; Silverman, 2000). Consequently, qualitative research is better suited at offering the essential in depth and exploratory tools required to gain a rich picture of the processes of how and why of a phenomenon occurs (Symon and Cassel, 1998). Particularly as qualitative research in business environments offers a stronger foundation for analysis and interpretation, being grounded in the phenomenon's natural environment (Collis et al. 2003).

The study focuses on BI, which derives from the field of IS therefore the endorsement of the qualitative research approach by IS researchers has also guided the orientation for this research. It is evident from the extant literature that IS research favours the qualitative approach. There are complications of capturing the complexities of social and technical elements in the field of IS into quantitative statistics, as a result, the use of qualitative research in the field of IS research has continually gained momentum (Goldkuhl 2012). It is thus argued that the need for more open and nuanced approaches to studying and analysing the complex nature of IS is being met through the application of qualitative traditions. Additionally, Orlikowski and Gash (1994) posit that in IS research, the adoption of qualitative approaches is suitable for extracting people's interpretations of technologies and their actions around them. The foundations of this research are centred on the actions and interpretations of BI users, regarding their use of BI technology therefore the qualitative approach is appropriate.

The qualitative premise for this research follows in the steps of a series of significant previous qualitative IS studies (Mumford et al. 1985, Nissen et al. 1991, Lee et al. 1997, Trauth 2001, Myers and Avison 2002, and Kock 2007; Ponelis 2015; Shollo and Galliers 2016). Furthermore, several special issues of journals covering qualitative research papers or methods within such qualitative traditions have also been previously well publicised; (Myers and Walsham 1998; Kock and Lau 2001; Baskerville and Myers 2004). The central premise of IS research knowledge is concerned with understanding through processes of interpretation. Consequently, researchers are required to

interpret *the 'existing meaning systems shared by the actors'* (Orlikowski and Baroudi, 1991:15). It is due to these centrally emphasised elements of systems research that supports the interpretivist, qualitative position of this research. Particularly as interpretivism focuses on working with the subjective meanings that are prevalent in the social world, by acknowledging their existence, rebuilding and understanding them, in avoiding to distort them and to utilise them subjective meanings as foundations in theorising (Goldkhul 2012).

4.4 Research Strategy – Case study

The case study approach can be defined as an empirical inquiry which investigates a contemporary phenomenon in a real life context, where the phenomenon cannot be isolated from the context in which it is embedded (Yin 1989). Case studies, dependent on the type of research question being addressed, can be listed in three basic categories of being either exploratory, descriptive or explanatory (Yin 2009). Furthermore, case studies can be referred to as a research which examines a few cases or more often a single case, but in a lot more detail (Gomm et al. 2000). Accordingly, this research adopts the exploratory style of case study research; through focusing on 'how' and 'why' questions relating to the role of BI in impacting organisational dynamics within a public sector healthcare context. Yin (2003) states, if the available literature on a topic is scarce, an exploratory case study would be ideal to expand the field of empirical knowledge. The exploratory case study research is thus also credited with scoping the direction of future research, particular case study research with emerging areas of study (Roethlisberger 1977). As highlighted in the earlier sections, there are a lack of BI studies from an internal organisational context which focuses on human factors and issues of power dynamics. Thus, the dearth of existing research in this area, compounded by the call for more human-centric perspectives on BI decision-making, provided the rationale for an exploratory case study approach. Therefore, in line with this criterion, this research can also be considered as a

nascent, emerging area which requires further examination through exploratory research.

4.4.1 Research logic and Case study

The logical arguments which underpin the process of research enquiry can be categorised as either deductive or inductive (Eisenhardt and Graebner, 2007). Both of these are approaches to the relationship between theory and research. In inductive reasoning, the theory is generated following research, while in the deductive approach, research is conducted with reference to either hypotheses or propositions, with ideas generally being inferred by the theory (Bryman 2012). Case study strategy may be used for a number of reasons, such to describe a phenomenon, theory building, test theoretical concepts and relationships, or in order for all three (Remenyi 1991). Furthermore, case study is also appropriate for exploring theoretical propositions (Teegavarapu et al. 2008). There is also the need to apply deductive logic where the research propositions are tested through the comparison of the emergent data with previous literature and hypothesised links between the identified factors and outcomes. Many scholars have supported the application of case study from a deductive logic for the purposes of testing theory (Benbasat et al., (1988; Yin 2009). Accordingly. this research also implements a deductive case study strategy to describe a phenomenon (i.e. impact of BI use on organisational power dynamics) and test theoretical concepts or relationships (i.e. proposed 6 research propositions cited earlier).

4.4.2 Rationale for Adopting Case Study Research

According to Denzin and Lincoln (1994) the empirical resources of Qualitative research consist many of case studies, personal experience, observational and visual texts elements. The use of case study as a research methodology is widely used in various disciplines, from studying individuals from a psychology and plethora of social contexts, through to examining organisations, particularly from IS contexts (Davies 2007). The case study research offers a degree of flexibility, when compared to other qualitative approaches such as phenomenology or grounded theory, as case studies are typically designed to suit a case and research questions (Hyett et al. 2014). The qualitative case study is largely chosen by researchers that are interested in discovery, insight and interpretation, as opposed to testing hypothesises (Merriam 1998), as also is the case in this research.

The case study methodology is accepted as the most common qualitative method used in the field of IS (Myers 2003), which is reflected by the long tradition of interpretative case study methodologies used in IS research (Markus, 1983; Suchman, 1987; Zuboff, 1988; Boland and Day, 1989; Orlikowski, 1991; Walsham, 1993; Orlikowski and Robey 1991, Jones and Nandhakumar 1993; 2002; Walsham and Waema 1994; Suchman 1987; Shollo and Galliers 2016). This therefore justifies that IS research which characteristically involves people and technology, opt for interpretive case studies.

Arnott and Pervan (2008:667) endorse the interpretive case study methodology, stating that it increases the relevance of research since case studies *'can illuminate areas of contemporary practice in ways that studies such as laboratory experiments and surveys cannot.*' The use of case study methodologies are ideal for IS research as the research questions IS researchers and practitioners are typically interested in are concerned with the actions and outcomes stemming from the interactions between IS and people, thus focusing on organisational elements as opposed to merely technical aspects. It is due to this category of inquiry that case study methodology is

most suitable for IS research (Iacono et al. 2011), as also reflected by the research objectives and focus of this research.

Pertinently, Shollo and Galliers (2016) can be credited for opening up a new departure in BI literature. Their study revealed the role of BI systems in creating organisational knowledge, in which they developed a conceptual framework of BI organisational knowing, identifying specific practises triggered by BI systems. Their adoption of a case study methodology allowed them to yield deep insights into how BI systems were able to initiate problem articulation, dialogue and the practise of data selection. Importantly, their empirical base for the study was an illustrative interpretive case study, focusing on knowledge creation through BI technology. By adopting this research methodology the study was able to identify and hone into previously untended areas of BI. Therefore this research also aims to contribute to this new stream of BI literature, by following in the methodological steps taken by Shollo and Galliers (2016).

Case studies can be exploratory, descriptive or explanatory in their nature (Yin, 1994). When the purpose of a study is to gain an understanding into a phenomenon, as is the case in exploratory research, case studies are the most suitable method (Levy and Powell, 2005). Consequently the research methodology opted for this research is an exploratory case study methodology. The case study methodology is the favoured approach when the phenomenon requires examination from within its natural setting. Therefore, the focus of the case study approaches in on ongoing events along with the experiences of the actors (Iacono et al. 2009). This is ideal for the purposes of this research as the phenomenon of BI and the way in which its various users practise this technology can be understood more closely from within its natural setting, the organisational environment itself. This methodology is also justified as case studies place emphasis on the actors and their experiences, appropriately in the context of this study the experiences and cognitive elements of BI users, namely the analysts and functional managers are the

primary focus, as opposed to the technology, therefore further justifying this methodological choice.

As highlighted earlier, although qualitative research, particularly case studies can be conducted adopting a positivist philosophical position (Rezgui and Miles 2011), the case study methodology is commonly associated with either interpretivism or pragmatism (Sexton and Barrett 2003). Furthermore, while analysing research methodologies in line with philosophical underpinnings, Sexton (2007) concludes that the case study methodology is closely linked to the idealism/interpretivist viewpoints. This therefore establishes that along with the qualitative orientation, the choice of case study methodology is also compatible with the philosophical positioning of this study.

In addition, while Qualitative research aims to gauge deeper, thick insights and descriptions, the case study methodology also provides the ideal platform to yield rich descriptions of social phenomena, thus generating knowledge of a phenomenon from within the interpretivist paradigm (Walsham 1993; Macpherson et al. 2000). This is also in line with the philosophical positioning for this research. Consequently, these rich descriptions will in turn address the call of Sharma et al. (2014) and Shollo and Galliers (2016) for more empirical focus into studying BI from the context of its users, as opposed to solely the technology. A key feature of the case study approach is in its accommodation of a variety of techniques (Gerring 2007). Therefore, the multiple sources of data collection will benefit the study as it aims to not only understand the deep level of intuition BI users appropriate during their use of BI tools, but also explore the relationships between various organisational actors. The multiple methods of data collection will consist of semi-structured interviews, participant observations and artefact reviews and are discussed in more detail section 3.5.1.

4.4.3 Case selection: Purposive sampling strategy

The case selected for this research is a NHS Trust, based in the UK. The random selection of cases is not good practise (Eisenhardt 1989), as a result purposive sampling was used to select the case for this study. The use of purposive sampling is common in qualitative research. According to Patton (2002), it is a widely used sampling technique for identifying and selecting information-rich cases, with the use of limited resources. This technique aids the identification and selection of participants, or groups of participants that are equipped with knowledge or experience relating to the phenomenon being investigated (Cresswell and Plano Clark 2011). As a result, the NHS trust selected for this study can be regarded as being information rich, particularly given that a total of seven hospitals and medical institutions operate within this NHS Trust.

4.4.4 Case Study Approach: Single versus Multiple Case Study Research

Yin (2009) posit four types of case study designs which include; single case (holistic); single case (embedded); multiple cases (holistic), and multiple cases (embedded). The use of single case study is considered suitable if the study is either a critical case, extreme/unique case, revelatory case, representative/typical case and longitudinal case. Accordingly, a researcher must decide whether a research question can sufficiently be explored within a single case analysis or if multiple cases are required, therefore the context of the case and its nature matters. The researcher appreciates the methodological rigor of a case study associated with multiple cases (Miles and Huberman 1994). However, the single case research is also credited for its descriptive power and attention to context (Shakir 2002), and these elements are vital in the context of an exploratory study. Furthermore, NHS, the case selected for this research is the fifth largest employer in the world (NHS Choices 2013). Due to their large and complex orientation, the NHS is information-rich, possessing a great deal of information which is sufficient for the requirement of the research.

Additionally, IS researchers have seen to favour single case studies as it allows in-depth analysis of one setting with regard to a large number of aspects, thus allowing for a comprehensive and detailed analysis of organisational dynamics, and the production of the rich descriptions favoured by interpretive researchers (Doolin 1996). A multiple case design is usually associated with sacrificing detail and richness of description for the purposes of making comparisons across several setting. Benbasat et al. (1987) further states that multiple case design are more desirable with the intent of the research is either description, building theory or testing theory.

Furthermore, Yin (2009) states that single case studies are more suitable at the commencement of theory generation and testing, as it enables researchers to imbed into the research, adjust to the settings and begin to understand the environment, jargon and contingencies of the context which they intent to research; something akin to Bonoma's drift stage (Myers & Avison 2002). Besides, it is argued that single case studies are often used as precursors to multiple case studies, such as a pilot study (Benbasat et al., 1987), therefore it is not a question of definitively picking one over the other.

Varying views exist relating to the use of single case vs multiple case design, for instance the advocates of the latter argue that findings resulting from multiple case studies are fundamentally more reliable than from single case study. This is underpinned by the notions that data derived from multiple contexts assists in making the study more reliable and replicable (Herriott and Firestone, 1983). Conversely, it is argued that the deep-seated insights and in-depth knowledge that can result from single case studies compensates and overcomes the criticism relating to lack of comparisons across contexts (Gerring 2007; Mahoney 2000).

While multiple cases studies are credited with allowing for variations beyond individual studies for comparison purposes, thus allowing for some degree of comparison and cross referencing. Yet, there is no agreement between scholars on the most favourable number of case studies, for instance some state a maximum of ten (Gable 1994), others suggest between four to ten

(Eisenhardt 1989), therefore the choice of how many case studies to incorporate as part of a multiple design is often left at the discretion of the researcher. In addition, Dyer and Wilkins (1991) also discuss the dichotomous nature of single and multiple designs and posit that insights derived from a single study can offer more valuable insights than multiple studies, as the former places emphasis on the richness of data over comparative ability and explanatory power associated with multiple cases.

The case study offers researchers more freedom than other research designs in terms of utilizing various data collection techniques and methods, with the aim of achieving a more rounded and comprehensive understanding (Hakim, 1987). While it is acknowledged that case study research allows for an in-depth account of a phenomenon through multiple forms of data collection, Parkhe (1993) highlights that amassing large amounts of data can result in complex theories thus compromising precision in the process. However, the researcher aims at addressing these challenges by firstly, aligning questions from the interview agenda, with the proposed propositions of the research, thus overcoming issues associated with collecting large quantities of data (See appendix D) Furthermore, case study research also presents challenges due to its fluidity and lack of boundaries between 'process', 'events', and 'time'. The researcher aims by addressing this through setting appropriate boundaries, processes of interests to the research and by fixing a realistic time frame for the study prior to commencement (Creswell, 2006). Accordingly, this research will opt for a single case study design.

4.5 Data generation

This section of the methodology chapter offers insights into the data generation phase of this research. Data generation consists of using multiple sources of data (Pettigrew, 1985), which is considered essential in case study research (Yin 1989). Merriam (2002), posits the key techniques for data collection in a qualitative research include; interviews, documents and observation. To gain a complete and in-depth insight into how BI impacts

organisational power dynamics, semi- structured interviews and documents review was used. In addition, field notes from observations were also applied to triangulate the findings and to support with understanding contextual factors. The data collection methods and lines of enquiry for this research included acquiring insights through corporate documentation, reports, meeting minutes, Care Quality Commission (CQC) guidelines, informal conversations; policy documents, minutes from meetings as well as email exchanges between functional managers and analysts. Table 4.1 offers a list of the data sources utilised in this study. By following such approach enhanced the reliability of the research and offered contextual insight which may otherwise be missed through merely using interviews. It is also noted that the findings derived from these sources were double-checked with the NHS trust on several occasions, as part of the triangulation process to further validate the results.

Empirical materials	Media	Explanation
Meeting minutes	Electronic/paper	• Meetings between in-house analysts and Functional managers • Meetings with clinicians and Functional management • Informatics and Performance meetings consisting of Senior analysts
Interview transcripts	Electronic/paper	• Interviews with functional managers and data analysts
Documents	Electronic/paper	• NHS Digital Strategy report • IT Corporate Strategy • Wachter Report (2016) • Care Quality Commission (CQC) guidelines • NHS Website

		• Communications Strategy • Fieldnotes • Reflections from participation in activities.
Emails	Electronic documents	• Scheduling and planning emails • Interactions between functional management and analysts

Table 4.1: Source of data collection

4.5.1 Semi Structured Interviews

The interview method is a managed verbal exchange (Ritchie and Lewis 2003) and regarded as the 'gold standard' of Qualitative research (Barbour 2003). The interview method can be placed on a continuum which ranges from structured interviews through to unstructured interviews. However, the semi structured interviews will be used in the case study (Wengraf 2001) for various reasons. The context and focus of this study is centred on exploring deep level intuitiveness and cognitive elements of BI users, therefore requiring a method that warrants in-depth analysis, thus the semi structured interviews are appropriate for this. This method provides opportunities to explore issues that may materialise during interviews, particularly significant symbols that actors use in their attempts of mean-making. While the semi structured interviews will follow an interview guide, this method of interviewing also allows the researcher to follow topical trajectories in the discussions, which may drift away from the interview guide, yet be appropriate in uncovering deep insights into particular issues.

The nature of the semi structured approach is such that it encourages a conversational form of interviewing, thus creating rapport between participant and the researcher, as a result potentially yielding valuable insights.

Observational note taking will also be used during the face to face interviews (Welman et al., 2005), in order to capture any non-verbal communication that may be valuable in the context of the interview (Crang and Cook 2007). However, it must be appreciated that while interviews are well suited for the collection of rich data and producing meaningful insights, this is not automatically guaranteed (Schulze and Avital 2011). Therefore, other methods will be also used to alongside interviews for data collection.

4.5.2 Participant observation

According to Denzin and Lincoln (1994) one of the widely used empirical resources of qualitative research is observational research. Iacono et al. (2009) outline that participant observations are most commonly carried out in ethnography and case study research. However, it has not been widely utilised in the field of IS, though some IS studies have reaped benefits from its use. For instance, Zuboff (1988) utilises the participant observation detailed in his work *'In the age of the smart machine'*. Others in the IS field argue that interviews are also a form of participant observation (Duhan et al. 2001), while some IS researchers have combined the use of interviews with distant, passive observation of meetings and testing sessions (Pollock and Cornford 2004), other researchers have fully engaged and immersed themselves in their role as participant observations (Nandhakumar 2002). Yet, IS research should embrace and accommodate more observational research. Particularly as IS studies focus on phenomena as well as workplace behaviours, therefore, it is contested that the use of observations can uncover element beyond what interviews or surveys can achieve (Moore and Yager 2011).

The participant observations will be utilised for this study due to several factors. Firstly, Giddens (1984) argues that in reality, people know more than they can express, while it is also contested that unarticulated meanings in nods and silences should be looked into (Altheide and Johnson 1994). Thus, Moore and Yager (2011) claim the use of participant observations can enhance the IS research, by providing 'thick descriptions' of various IS phenomenon.

Additionally, this research also intends to explore the implications of power considerations, and how they may affect the way in which BI is used by its users, thus observations may reveal elements relating to resource, process and meaning power (Hardy 1996; Luke 1974), which otherwise would be undetected during other data collection methods.

The literature review informs of potentially divergent interests between stakeholders, therefore it is argued that these elements may not necessarily come to the forefront during the participant interviews due to the nature of the theme, but become apparent during participant observations. The case study of Maitlis and Lawrence (2003) revealed conflicting interests between divergent stakeholder groups, while the participants were able to articulate their interests during interviews, Simpson (2009) argues that the data from the interviews can be further enhanced by going beyond transcriptions, and supplementing with sound recordings and field notes from observations, particularly as verbal, emotional and physical actions are gestures that add meaning to a context.

Therefore, while it is accepted that the researcher's active presence in observations is a central element of the method, the extent to which they participate differs (Cohen et al. 2011). Gold (1958) identified 4 theoretically possible roles; complete participant, participant as observer, observer as participant and complete observer. The researcher for this research will take the position of 'neutral observer' as proposed by Walsham (2005). The extent to which the observer participates is dependent on a variety of factors, such as epistemological approaches, the nature of research and the availability of relevant conditions and resource.

Walsham (2005) explains that the neutral observer does not refer to being 'unbiased', as everyone is bound by biases of their own background, knowledges, and prejudices to view things in particular ways and not others. 'Neutral' refers to when the participants in the field do not identify the researcher as being associated with any particular group or individuals within the organisations, nor as having strong pre-existing views of individuals,

systems or processes as a result of previous endeavours in the organisations, or for the researcher not having or being interested in monetary gain, as for instance consultants may. Therefore, the involvement as researcher in this case reflects the ‘neutral observer’. The researcher will therefore be present during meetings and decision making processes.

Yin (2003) also advocates observations and suggests that it allows a researcher to cover real information in real time, whilst also offering contextual benefits through being observant during the context of an event. Furthermore, observations are also considered useful for gaining insights into personal behaviours and motivations.

4.5.3 Documentation

Document review will be used for the study to provide background information regarding the BI systems that are used by the analysts and decision making management. This will include reviewing previous and contemporary meeting minutes (Myers 2009), reviewing communications between various actors, as well as the reviewing of systems documentation. The document review will be beneficial as it will help gain an understanding on how the systems are ought to be used therefore this can act as a guide when interviewing participants on their use of the systems, whilst also offering insights into technical operations whilst also indicating culture (Yin 2003). Along with systems documents, other documents will be also reviewed such as project documentation. The document review serves the purpose of not only equipping the researcher with contextual insight into the organisation, but also highlights an analysis of previous actions and events, that may be raised by the participants during the interviews. The documentation review can also assist in revealing issues not previously noted, therefore making this a justified, unobtrusive choice for data collection.

Another source of data used in this research is documentation. It is not uncommon for documents to be used as part of a qualitative study, which can

take the form of unpublished or published printed materials. According to Silverman (2001), they can include governmental reports, company reports, letters, electronic communications and newspaper articles. One of the benefits of using documentation as a data collection method is its availability, which can be a source of immense data which may offer important insights into the topic being researched. With the focus of the research at hand being the impact of BI use between organisational actors within the healthcare sector, this research utilised physical internal documents relating to BI strategy and policy as well as through the use of electronic communications between actors, such as emails. Moreover, national policies such as 'NHS Five Year Forward View', 'Wachter Report (2016) were also reviewed. In agreement, Pettigrew (1990) argue the use of documents and materials provides a research with a more comprehensive view of the phenomenon of interest.

Accordingly, documents included NHS Digital Strategy report, NHS Digital Strategy report, IT Corporate Strategy, Wachter Report (2016), Care Quality Commission (CQC) guidelines, NHS Website, Communications Strategy and Fieldnotes . The use of these sources allowed for a degree of triangulation between data sources and also offered empirical depth into the findings which reveal how the use of BI impacts organisational power dynamics within the NHS.

4.5.4 Pilot Study

Empirical data was largely collected through conducting in-depth semi-structured interviews with key organisational actors from within an NHS ward and also through the use of participant observation (Atkinson and Hammersley, 1994; Myers et al., 1997). This allowed for insights into the increasing role of BI from within the healthcare and its impact of organisational dynamics was also gathered. In order to validate the research design and confirms its validity, an initial pilot study was conducted prior to the actual empirical data collection and in order to generate an initial understanding of

how BI is used within the NHS by its various organisational actors. This consisted of seven semi-structured interviews being conducted between January 2018 – March 2018, of four service managers and three business analysts. The pilot study was originally carried out with service managers and data analysts from a different NHS trust, which therefore enhanced the overall quality of the research, as key issues such as uncertainty and vagueness from within the interview agenda could be identified. The interviews were recorded and subsequently transcribed.

The entire process of conducting the pilot study assisted in developing and amending the interview protocol used in this research. Furthermore, conducting the pilot study proved highly useful as it also offered an awareness into how the participants perceived the research and that the topic being explored was of relevance. Moreover, it must be noted that while the NHS trust used for the pilot study did use BI, it was not widespread, with much reliance on advanced excel for analysis purposes therefore the findings from the pilot study are not reported as part of this research. Nonetheless, it still helped identify the appropriate end-users from within an analytics and decision-making context. Additionally, this study also allowed the researcher to gain substantial insights into numerous issues relating to the context of BI use, which previously were only understood through literature. Thus, the pilot study offered practical contextual insights which helped understand the application of BI within the healthcare sector, which was also reflected in the interview protocol. Furthermore, the pilot study presented some key learning for the researcher, such as appreciating that factors such as interview cancellations and equipment failure could have detrimental impact on the research. Therefore, through experiencing this the researcher ensured that participants had a choice of several appointments to choose from during the empirical stages of the research, as well as ensuring a spare recording device was taken during site visits. These measures helped with establishing the overall reliability of the research.

In order to make sure that the data generation was relevant for the purposes of the research, the researcher developed an interview protocol for the seven

participants of the pilot. This interview protocol allowed the researcher to probe in great detail into healthcare activities, NHS regulatory bodies, as well as various contextual details such as how the Clinical Commissioning Groups (CCG) operate. Most importantly, the pilot study provided insights for the researcher into the types of organisational actors within the NHS, their responsibilities and their use of BI systems. Accordingly, the interview protocol also allowed for the replication of the interview process, thus also ensuring reliability (Yin, 1994).

According to Pettigrew (1997), interview protocols are typically tested and polished at the early stages of conducting interviews. Therefore, the protocol used in this research was put to the test in the pilot study, which following amendments, led to the overall improvement of the interview agenda, that was then used within the NHS trust to help collect rich but also relevant case study data, by allowing the researcher to guide the interview process and ask consistent questions. The chosen case organisation, being an NHS Trust for this research was suitably selected due to the prevalent use of BI systems, unlike the case organisation used during the pilot study, where the use was scanter. Although this may raise issues concerning generalisation to a wider population of NHS trusts, the literature review conducted, and the model developed are vital tools to place the findings of this research in a wider context.

4.5.5 Protocol development

Yin (2009) emphasises the need for a case study protocol, which acts as a guide for researchers in conducting case study research. More specifically, a case study protocol can be described as a set of guidelines which helps structure and govern a case research study (Miles and Huberman, 1994), which include clearly stating the procedures and instructions which determines the way in which the researcher and the research project is conducted (Yin, 2009). The proposed research instrument for collecting data during the case research is also acknowledged as part of the case study protocol. By abiding

by a case study protocol enhances the *reliability* of case study research, allows the researcher to carry out the case study in a rigorous manner (Runeson and Host, 2009) and enhances communication between researcher and the research participants (Miles and Huberman, 1994). Accordingly, the case study protocol for this research in line with the guidelines provided by Yin (1994) consists of 4 sections. The first section focuses on the overview of the study, including the research objectives and rationale. The second section covers the field procedures and ethical issues, including aspects relating to audio recording and confidentiality issues. The third section focuses on the questions addressed by the research and finally, section 4 of the case study protocol includes the outline and format of the research report.

4.5.6 Interview process

The researcher also provided an information sheet and consent form, which highlighted the agreement of confidentiality and anonymity of the participants, duly signed by the researcher and his supervisors (see appendix A and B for a copy of the document). Pettigrew (1997) highlights it is good practice to confirm the date, location, and time of interviews between the researchers and the interviewees beforehand, accordingly the researcher endeavoured to achieve this. The semi-structured interviews for this research were conducted using a formal interview agenda (Appendix C). This section provides insights into the interview process which was implemented for the 30 participants for this study. Before conducting the interviews, the researcher provided several documents including an overview of the research agenda, objectives and research methodology to the participants a week prior to the scheduled interviews. Additionally,

In accordance to the aim and objectives of this research, the participants of this research were selected using two of the following categories; firstly, the departments which involved generating BI analysis and BI decision-making and secondly, the position, in terms of participants who held decision making

responsibilities as well as those whose role required active utilisation of BI. It is argued that the typical concern of IS researchers has been IT specialists at the workplace, a group that is often disregarded, frequently with damaging consequences (Peppard and Ward 1999). Accordingly, the BI analysts with specialist technical skill sets (IT specialists) are integral to this research. Therefore, both the direct users (analysts) and secondary users, (functional managers) were considered important units of analysis. Accordingly, the interviews were conducted with functional managers and experienced BI analysts and took place face to face in separate meeting rooms, therefore allowing the participant to openly engage in a conversation without any disruptions. Each interview lasted approximately between 45-60 minutes. The Table 4.2 provides a breakdown of the participants for this research by their role, keeping confidentiality in mind, the case organisation in this study is referred to as “NHS Trust”.

Who	**Where**	**Interview duration**
General Manager (J.W)	NHS Trust Ward	45mins
Senior Information Manager (S.A)	Performance and Informatics Department	45mins
Performance Manager (M.G)	Performance and Informatics Department	45mins
Service Manager (J.T)	NHS Trust Ward	45mins
Service Manager (N.A)	NHS Trust Ward	45mins
General Manager (T.H)	NHS Trust Ward	45mins
Director of Operations (S.A)	NHS Trust Ward	45mins
Service Manager (J.A)	NHS Trust Ward	45mins
General Manager (G.M)	NHS Trust Ward	45mins
Assistant Director of Ops (A.W)	NHS Trust Ward	45mins

Central Business Analyst (S.K)	Performance and Informatics Department	60mins
Performance & Improvement Manager (R.J)	Performance and Informatics Department	75mins
Cardiovascular Information Manager (J.D)	NHS Trust Ward	67mins
Central Business Analyst (S.G)	Performance and Informatics Department	40mins
Service Manager	NHS Trust Ward	60mins
Informatics Enterprise Architect (S.S)	Technical Architecture & Strategic Planning	32mins
Senior Technical Strategy Analyst (J.L)	Technical Architecture & Strategic Planning	60mins
Central Data Analyst (J.R)	Performance and Informatics Department	35mins
Central Data Analyst (C.S)	Performance and Informatics Department	45mins
Clinical Coding Analyst (S.P)	Coding and Performance Department	90mins
Central Data Analyst (P.S)	Performance and Informatics Department	50mins
Senior Central Analyst (P.S)	Performance and Informatics Department	45mins
In-house Analyst (R.L)	NHS Trust Ward	55mins
Associate Director of Operations (L.B)	NHS Trust Ward	60mins
Business Manager (S.C)	NHS Trust Ward	60mins
Deputy Service Manager (R.G)	NHS Trust Ward	60mins
Performance Manager (P.G)	NHS Trust Ward	75mins
In-house Data Analyst (J.J)	NHS Trust Ward	65mins

Business Intelligence Officer (M.B)	NHS Trust Ward	45mins
Service Manager (J.A)	NHS Trust Ward	60mins

Table 4.2: Research participants breakdown

During the interview process, it was noted by the researcher that by interview number 21, similar themes were surfacing during the interviews. Therefore, the researcher decided to draw a close to collecting further interview data. However, it was during the qualitative thematic analysis process that further codes and themes were emerging, which were not immediately identified by the researcher during the interviews. This prompted the need to collect further interviews, to ensure that key insights were not being overlooked. Thus, following this iterative process, a total of 30 participants were interviewed as part of the interview data collection process.

4.5.7 Integrity of the Case Study Strategy

Reliability and validity are the criteria by which research is commonly assessed. The focus of qualitative research however is placed on the degree to which the researcher provides evidence that the insights and analysis amount to the reality of the studied individuals and situations (Creswell, 2009). Therefore, terminology used to assess qualitative research may differ to that used in quantitative research, reflecting the difference in the nature of these orientations. As a result of the nature of interpretive research, emphasis shifts towards the researchers approach, participants' involvement and the means by which the data is interpreted and subsequently presented (Altheide and Johnson 1994). As such authors have advocated divergent standards for assessing qualitative studies (Merriam and Goetz, 1982; Janesick 1994; Guba and Lincoln 1985;1994; Golden-Bidle and Locke 1993; Altheide and Johnson 1994; Klein and Myers 1999; Whittermore et al, 2001 Creswell 2007; Tracy 2010).

It was imperative for the researcher to address internal validity in order to guarantee the findings of this research were robust, due to the use of interviews, documentary sources, and observation. In doing so, the researcher ensured each interview was digitally recorded and also accurately transcribed. The participants were subsequently given a copy of the transcribed interviews for reviewing purposes, so any inconsistencies that may have emerged could be resolved and to also eradicate any interviewer bias. Furthermore, caution was taken by the researchers to ensure that the data collected during this research converged around similar facts rather than emotion due to the array of evidence collected in this research. The measures taken in this research, such as conducting a pilot study which informed the interview protocol as well as the use of a case study protocol contributed towards the reliability and validity of the study. Furthermore, the triangulation of data through the use of more than one data source is highly recommended by many researchers (Miles and Huberman, 1994; Carter et al. 2014; Yin, 2009) as a means for enhancing both the reliability and validity of qualitative research (Chau, 1999). Accordingly, this research also followed procedures in conducting this research and through triangulation of data collection methods, contributed to the reliability and validity of the study (Stoecker, 1991; Yin, 2003). Therefore, the researcher has full confidence in the accuracy of the research process and the findings.

4.5.8 Ethical considerations

Upholding ethics is key for any research, as too for the research at hand. This research was conducted in line with the University's ethical guidelines, through ensuring the research procedures addressed issues relating to the confidentiality and rights of the research participants, data security, anonymity, informed consent as well as the right to withdraw from the study at any point prior to the research analysis stage. The participants were made aware of this through the information sheet and consent form. A signed copy of the information sheet and consent form was retained by both researcher and

participant. The researcher ensured there were no invasion of participants privacy, therefore the interviews took place at the discretion of the participants at a location of their choice, on a one to one basis. The interview protocol was examined by the Research Ethics Committee at the University of Bradford whom subsequently granted ethical approval for the proposed data collection methods and modes of collection. Furthermore, the case organisation also agreed for the findings of this research to be published provided that their anonymity was upheld. Accordingly, this organisation is referred to as an 'NHS trust' without specifying which Trust or its geographic location

4.6 Data analysis

Creswell (2009) posits that during the data analysis phases, attempts are made by the qualitative researcher to understand and interpret the meaning the research participants place on the phenomenon. There are many approaches to analysing qualitative data such as grounded theory, content analysis and thematic analysis. However, Miles (1979) describes qualitative data analysis as 'attractive nuisance', commenting here on the attractiveness of the richness locked in the data, yet the difficulty of finding analytical routes through to that richness. Therefore, selecting an appropriate approach to analysing the data is paramount. Thematic analysis will be used to analyse the data for this research. According to Braun and Clarke (2006) thematic analysis is the foundational method for qualitative analysis. Thematic analysis is widely used in a systematically, yet flexible manner to identify themes that are entrenched in data sets. This form of data analysis will explore the different versions of the phenomenon as understood by the analysts and decision makers.

Boyatzis (1998) outlines two approaches to conducting thematic analysis. Thematic analysis can be conducted using a theory-driven approach or a data-driven approach. Both approaches are used to develop themes and aid researchers to formulate theoretical concepts or advance theory. While thematic analysis can be approached from either ends of the spectrum,

Boyatzis (1998: 37) states that between these dichotomous ends of the spectrum is the prior-research-driven theme which involves reviewing literature to in order to provide “insight into the possible development of a thematic code development approach”. Furthermore, these approaches can be combined and used in a hybrid approach, integrating theory driven codes with inductively data driven codes (Muir-Cochrane and Fereday 2006).

The data analysis approach for this research will consist of using concepts derived from the literature as sensitising lens to explore and make sense of the data while also developing themes from the data. This is in accordance with the recommendations by Walsham (1995) of applying previous knowledge as ‘scaffolding’ in an interpretive study. Therefore, the research will maintain a degree of openness to the data collected, while also being willing to adjust initial assumptions and theories.

4.6.1 Analysis process

The concluding phase of the research methodology, involves the data analysis and the testing of the research propositions. The multiple sources of data collected from the case study were triangulated and subsequently analysed to draw empirical conclusions. This research implemented a qualitative thematic analysis and used NVivo software to facilitate the development of the manual coding system used for data analysis. The data analysis consisted of going through the interviews in order to examine the meaning of peoples’ words and actions (refer to Ramanath, (2009). The data analysis and synthesis were essentially an iterative process, as ideas became apparent and common themes were identified and shaped into a coherent analysis. This process was in line with the recommendations forwarded by Braun and Clarke (2006) as also graphically depicted in Figure 4.1.

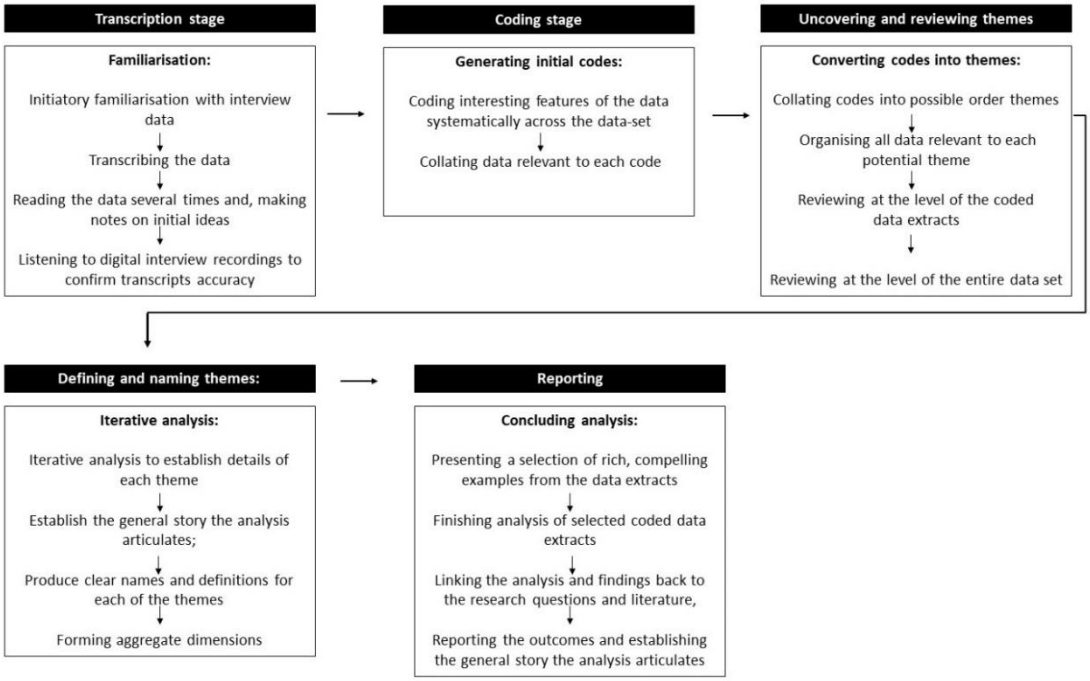


Figure 4.1: Thematic analysis process

It is noted that although transcribing can be a time consuming and monotonous task, it is highly useful at familiarising the researcher with the data (Riessman 1993). Bird (2005: 227) refers to transcribing as *"a key phase of data analysis within interpretative qualitative methodology"* Therefore, following the transcription, the mass of qualitative data will be organised by selecting, focusing, simplifying, abstracting, and transforming the data through writing summaries, coding, generating themes and creating categories etc. While the aim will be to disregard any irrelevant information, such information will be stored and re-examined if required later. The aim will be to retain the information in such a way that it is true to its original nature, therefore accounting for subtleties picked up during the interview, as they may alter the meaning of what is intended (Poland 2002).

During the transcribing process, initial codes will come to surface from the data. According to Boyatzis (1998: 63) codes are *"the most basic segment, or element, of the raw data or information that can be assessed in a meaningful way regarding the phenomenon".* The use of coding also referred to as indexing is considered as the starting point of analysis for most qualitative

studies (Bryman 2012). Furthermore, Miles and Huberman (1994) state that the coding process is integral to analysis. The process of coding typically involves catergorising data that share similar meaning. Therefore, linked units of data are created during the coding process, which can either be an emergent approach which is data driven, similar to the grounded theory approach or more theory driven. In emergent coding, themes emerge following an iterative process of reviewing, comparing and scrutinising the data. On the contrary, codes are guided and derived from the literature, and used during the data analysis stages.

These codes guide the data collection and analysis, and therefore are expected to develop further during the search of themes as during the stage of analysing the data codes and searching the themes, patterns and relationships are expected to constantly develop. Following the process of coding, the following phase is concerned with the development of themes. It is at this stage where interpretative analysis of the data occurs, whereby arguments relating to the phenomenon in question are made (Boyatzis 1998). The whole data will be thoroughly analysed, paying attention to all aspects of the data, with the aim of identifying interesting and recurrent patterns in the data while also identifying themes that link with the reviewed literature.

Therefore, similar codes will be organised together into same first order codes. In line with this approach of linking the codes, linkages between the categories of codes will be identified, leading to potential second order themes. The second order themes will then further be developed through the relationship held between the initial codes. This will involve revising, merging and even deleting first order codes where necessary. Themes shall also be reviewed and refined at this stage. The first level of reviewing involves the coded data extracts for each theme. If they cohere to a meaningful pattern, they remain and the next level of abstraction can take place, however if the extracted data fails to display coherence then the theme may be disregarded or the extracts within the themes should be revisited. The final phase through an iterative approach to the analysis will involve combing the second order themes into

aggregate dimensions that embody the overarching concepts relevant in this study.

4.7 Conclusions

In summary, this chapter started by discussing the philosophical underpinning of this study based upon the researchers ontological and epistemological assumptions and why these positions were ideal given what this research is set out to achieve. The chapter then established that the qualitative approach is the most suited given that this approach is widely utilised within the field of IS, specifically when exploring humans interactions with technology, accordingly, the interpretative qualitative approach was adopted. The growing importance of BI within the public sector, yet lack of insights into its implications from a human, power dynamics perspective has elicited the use of case study design, as this approach is highly recommended for studying a case in-depth. Following a detailed discussion of the chosen methods and data analysis approach, the principles of evaluating qualitative research were addressed. The selected case for this research was also briefly discussed; as well as addressing the research reliability and ethical considerations. The following chapter provides a comprehensive account of the NHS, the chosen case for this research.

5.0 CHAPTER 5: Context Chapter

5.1 Introduction

The case context within any research is highly important and can have major implications for the overall contributions of the research. This is more so the case in this research, particularly given that one of the rationales for conducting this research was due to the contextual relevance of the topic being investigated and its timeliness within the context of the NHS. The organisation as a whole is undergoing a digital transformation, which is aimed at transforming patient care with the effective use of IT.

Much of this strategising forward is as a result of the widely read ‘Making IT Work: Harnessing the power of health information technology to improve care in England’’ report by Professor Wachter (Wachter 2016), in which the

Department of Health and NHS England is advised to make the secondary care system more digital. In summary, he provides 10 core principles that require closer inspection and focus in order to help make this digital transformation a reality, as highlighted below:

- Digitise for the correct reasons
- Is it better to get digitisation right than do it quickly?
- Return on Investment from digitisation is not just financial
- When it comes to centralisation, the NHS should learn, but not over-learn, the lessons of the National Programme for IT (NPfIT)
- Interoperability should be built in from the start
- While privacy is very important, so too is data sharing
- Health IT systems must embrace user-centred design
- Going live with a health IT system is the beginning, not the end
- A successful Digital Strategy must be multifaceted, and requires workforce development
- Health IT entails both technical and adaptive change

(Wachter 2016).

While these recommendations are critical pointers for the NHS it can also be argued that these are resultant of previous, less successful implementation of Digitally-Enabled Service Transformation (DEST) initiatives for the NHS. Although digitisation within the GP sector has experienced more success, the sporadic computerisation of the hospital sector has resulted in digital transformation projects facing many challenges, therefore creating a significant barrier to transforming care. A notable example of such failure is the case of the National Programme for Information Technology (NPfIT), which launched in 2002 and ended as ‘the worst and most expensive contracting fiascos in public institution history’ (Syal, 2013), nine years later (Sheikh et al., 2015).

In line with the ‘NHS Five Year Forward View’, in which the organisation aims to operate largely paperless by 2020, as also challenged by the then Home

Secretary Jeremy Hunt, it is evident that while ‘Paperless’ or even ‘Paper-lite’ is possible, it is highly likely that it will not be achieved by 2020 (NHE 2017), further highlighted by (Digital Health 2017). Nonetheless, the organisation remains committed at transforming its services with the aim of largely operating paperless, as a data driven organisation, both currently and moving forward in the coming years. The Wachter report (2016) which reviewed the IT of the NHS firmly stipulates 2023 as being a more realistic target for a paperless operating environment. Therefore, given that the NHS is now strategised to collect more and more data, the ability of operationalising and creating meaningful insights from this data is highly important, as is the reliance on technologies such as BI. This NHS data drive can be considered pervasive, thus the effective utilisation of BI and other Data Analytics tools are pivotal in accomplishing successes from this abundance of stored data, not only for effective patient care, but also internally for achieving long-term goals for health and wellbeing at work, as reflected by the NHS England who are leveraging data analytics to create a tailored strategy to support the health and wellbeing of NHS staff (Scott 2017). Nonetheless, making effective use of the data and these tools isn’t without challenges, from both patient contexts and a clinical point of view (Cunningham 2017).

5.2 Case context: NHS trust

The name of the NHS trust used in this research is omitted for the purposes of this study, however, the wider NHS drive on digitisation and being data-driven is also a highly pertinent focus for this trust. The chosen NHS trust for this research is made of various hospitals and medical institutes, which total to seven overall. Accordingly, the participants from this research were selected from at least three of the hospitals operating as part of this NHS trust. The trust has a clinically-led structure, whereby clinicians and healthcare professionals play an active part in delivering services within the trust. Given the size and scope of the Trust, all the services are delivered under specific Clinical Service Units (CSUs) and are guided by a Clinical Director, a Head of a Profession and a General Manager, thus being led by a triumvirate team. In addition to

the medical teams, the trust is supported by a variety of other teams which include Estates and Facilities, Informatics, Finance, Human Resources, and Patient Administration. As such, the managerial structure of this NHS trust is depicted in Figure 5.1.

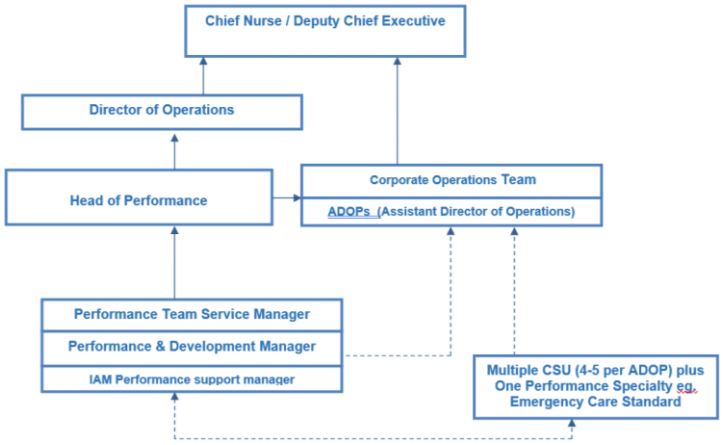


Figure 5.1: Case organisation structure

Moreover, in order to gain a further understanding of how this NHS trust operates, it is essential to provide a breakdown of the case NHS Trust in relation to all of its services across all the CSU's. Therefore, Figure 5.1 presents a decomposition of all the services within each CSU. Importantly, given the central focus of organisational actors, the key participants for the purposes of this research are functional managers, such as operational managers, service managers, who report directly to the CSU triumvirate leadership team, more specifically to the General Managers or Clinical Director. Furthermore, the other pertinent organisational actor for this research is the data analyst. These analysts operate across the trust, however are mainly part of the Informatics team, also referred to as the 'Central Performance and Informatics' team. Moreover, there are also other data analysts who work in the trust, though their paths cross, these analysts work independent of the central analysts' team, and are embedded within the services, such as the wards itself. These analysts are referred to as 'in-house analysts'.

5.3 NHS Power Dynamics

Power has many interpretations and manifests itself in many ways. According to Northouse (2012), power can be referred to as having "*the ability to affect others'* beliefs, attitudes, and courses of action". While various forms of power are present in all organisations, it is argued that from within a health care context, the exercise of influence and control is prevalent within hospitals, especially when organisational actors may compete for scarce resources, governance, mindsets and responsibilities (Abbott 1988; Kurunmäki 1999). The Organisation and Management fields of work continues to attract significant interest and analysis (Murphy 1990; Reed 1996; Ackroyd 1996; Freidson 2001). Currie et al. (2009) alludes to power dynamics and emphasises how managerial prerogatives and organizational controls are seemingly challenging the autonomy, legitimacy and power of professional groups (Clarke and Newman 1997; Exworthy and Halford 1999). Studies highlight that bureaucratic and managerial methods of organising work, are seen to create much tension between organisational actors such as professionals and managers, thus leading to hierarchy conflict as a result bureaucratic practices and an overabundance of supervision (Freidson 2001; Broadbent and Laughlin 2002).

The struggles of organisational actors in leveraging particularly forms of power is widely discussed from within the sociological literature (Abbott 1988), and also within works of professionalism (Freidson 2001). Waring and Currie (2009) also reflect such struggles between organisational actors from within healthcare, hospital settings, whereby management and professionals compete with one another for influence and autonomy. Such power standoffs are typically rooted in the management-expertise dyad, whereby management, who have process power attempt to manage medical professionals, who may not necessarily have control over the decision-making process, but certainly have expertise power. Thus, it is unsurprising that hospitals are referred to as professional bureaucracies (Carvalho and

Santiago 2016; Mintzberg 1979), wherein power exists in the form of knowledge and skill.

Accordingly, hospitals are attributed as having complex power structures, in which lower organisational actors may have more have authority over particular decisions, than functional management, who are ranked more superiorly (Spehar et al. 2014). Accordingly, in such organisational arrangements, it is argued that functional managers are required to recognise such dynamics when in discussions with expertise-bearing staff (Ham and Dickinson 2008). Although this interplay is largely in reference to management – clinical perspectives, similar intra-organisational dynamics can also exist between management and data analysts, as described by Shollo and Galliers (2016) during stages of articulation. The extent to the managers are able to negotiate with data analysts during BI decision-making processes can offer insights into power dynamics, particularly if one is able to influence the other, as it seems professionally skilled clinicians are able to. Accordingly, Braithwaite et al. (2004) add further to this discussion of organisational dynamics, by stating that managerial roles in such situations largely concern negotiation and persuasion as opposed to the exercise of formal control and authoritative command.

NHS management has traditionally been viewed from a two-fold perspective, as expected, its clinical managerial disposition, focused largely on workload and clinical duties, largely underpinned by professional and clinical values. The other being the operational branch of management, which overlooks the day to day, operational and strategic functionalities thus enabling the organisation to keep running (Paton 1995). As expected, this divergence, underpinned by varying socialisation stemming from clinician and operational focuses has seen to have created much tension over time (Owens &Petch 1995), largely as a result of divergent objectives. Such divergence is the result of general managers unrelenting driving clinicians to meet corporate rather than professional agendas (Hunter 1994). Similar to this clinician-managerial dyad, recent technological advancements have seen the rise for the need of

able-skilled data analysts, whom along with the top-down data-push initiatives imposed on managerial actors can be seen as potentially creating another paradigm within healthcare, that between management and analysts. Moreover, such top-down NHS initiatives are often associated with inadequate engagement and lack of local ownership on the front line, which are regularly seen as barriers to the success of projects (De Silva, 2015), and conversely, on occasions when top-down projects do witness a successful completion, it is often on a short-term basis, as without a thorough, underlying change in the behaviour of organisational actors, the results cannot be sustained (Day, 2004).

Additionally, such dynamics are also evident between clinicians and patients. The provision of knowledge, its subsequent acquisition, and the expectation to contribute personal preferences transpires in the context of a power imbalance between the clinician and the patient. Accordingly, the ability of a patient to actively partake in shared decision making not only links to how much knowledge they hold, but also relates to how they perceive their own power or influence in the decision-making. Thus, the patients perceived ability to apply this knowledge essentially dictates the likelihood and outcome of the articulation (Joseph-Williams et al. 2014). Therefore, stressing the importance of knowledge acquisition and confidence in its articulation when faced with a decision-making situation from a healthcare context. Thus, it is argued that further power play is evident between clinicians and patients themselves. Table 5.1 provides a breakdown of studies which have explored NHS decision-making.

NHS decision-making	**Description**	**References**
Shared decision-making	Decision-making shared between Clinical Professionals and patients	Barr and Elwyn 2016; Barr et al. 2014; Burges et al. 2008; Elwyn et al. 2010; Gravel et al. 2006; Homles-Rovner et al. 2000; Joosten et al. 2008; Joseph-

		Williams et al. 2014; Joseph-Williams et al. 2014; Stacey et al. 2008; Tai-Seale 2016)
Management-Clinician	Hybridity between managerial and clinician roles, whereby managers make both functional decisions as well as clinical related decisions	Correia & Denis 2016; Fulop 2012; Montgomery 2001; Kippist and Fitzgerald 2009; Hewison 2012; Savage and Scott 2004; Noordegraaf 2007; Kurunmaki 2004; Spehar et al. 2014; McGivern et al. 2015; Byrkjeflot and Jespersen 2014; Denis et al. 2015; Bode and Dent 2014

Table 5.1: NHS decision-making

The introduction and drive towards shared-decision making has been met with much reluctance on part of the professionals (Gravel et al. 2006), who often argue that 'shared decision making' essentially already occurs, therefore there is no need to further promote or emphasis this decision-making model, although such claims are contradicted by evidences (Burges et al., 2008; Elwyn et al., 2009). Nonetheless, the advent of BI has similar undertones in that in addition to the managers, the analysts are too becoming active contributors in shared decision-making.

5.4 NHS Electronic Patient Record (EPR)

The NHS are driving a number of initiatives in a bid to make decision-making more timely, transparent and inclusive of the organisational environment. For instance, a review of the Digitisation Strategy for the NHS and a review of relevant documentation highlights the NHS has aspirations of unifying systems through a single patient record system, referred as the Electronic Patient Record (EPR). The systems which will provide the streams of data to EPR are, the Lorenzo system, which is the patient record systems, the Electronic Document Management System (EDMS) which is system which converts patient case notes into an electronic format so that it can be moved around

and managed electronically on screen, and the proposed Clinical Portal. This is in line with the digitisation strategy implemented by the NHS. As such it was recognised that, in addition to the EPR, providing a single view of patient information, through the integration of the systems highlighted, Resource and Asset Management and Business Intelligence and Data Analytics is also central to this NHS trust's digital transformation. This is depicted by Figure 5.2.

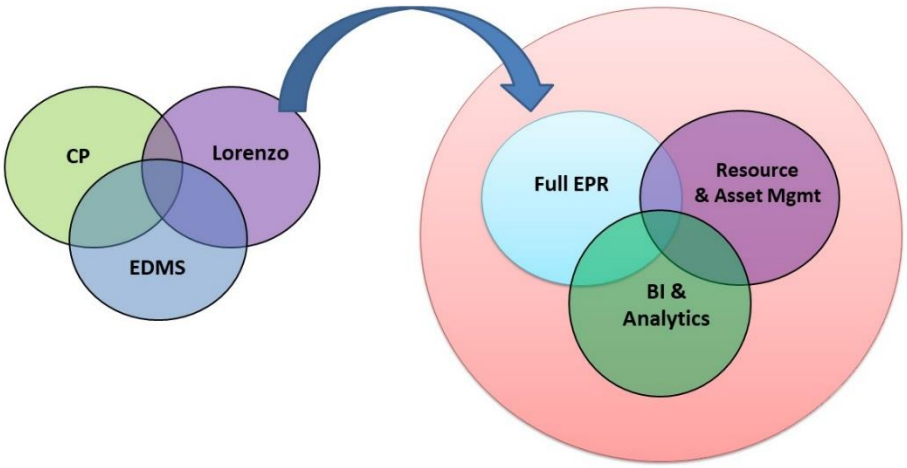


Figure 5.2: NHS Trust Strategy (Created by Author)

While it can be argued that the 'Full EPR' will bring about many benefits, it is underpinned by a clinical focus, concerned with providing a consolidated view of patient information and their care history. Similarly, Resource and Asset Management also has a clinical focus in that it is concerned with capacity utilisation, thus ultimately impacting the quality of patient care. However, it is primarily a key operational focus. Accordingly, it is argued that the BI & Analytics drive within the NHS is fundamental in facilitating key operational decisions within services and wards from resource planning and asset scheduling contexts. As such, this strategic vision of the NHS aims at providing high quality information, readily accessible for decision making purposes across the CSU's through the use of BI, which will assist in predicting, planning and efficiently managing services to deliver key patient care. This further emphasises the need for an exploration of how BI is currently driving decisions and being used by the organisational actors within this NHS trust. As such, this highlights that the 2020 strategy of digitisation goes beyond just

consolidation of data sources and EPR, and also centres on Resource and Asset Management and BI & Analytics.

Accordingly, as also highlighted in the methodology chapter, the participants for this research are also associated to these key areas of focus, through functional managers, ultimately responsible for the resource and asset management and the analysts, who form the BI and Analytics unit. Consequently, Figure 5.3 is a conceptual representation of the BI decision-making process in place within the NHS trust. It provides a breakdown of the key components relating to BI use within a healthcare context, by firstly acknowledging the disparate sources which feeds data to the organisation, the storage phases, which essentially leads to the cleansing and preparation of data for trust wide reporting purposes.

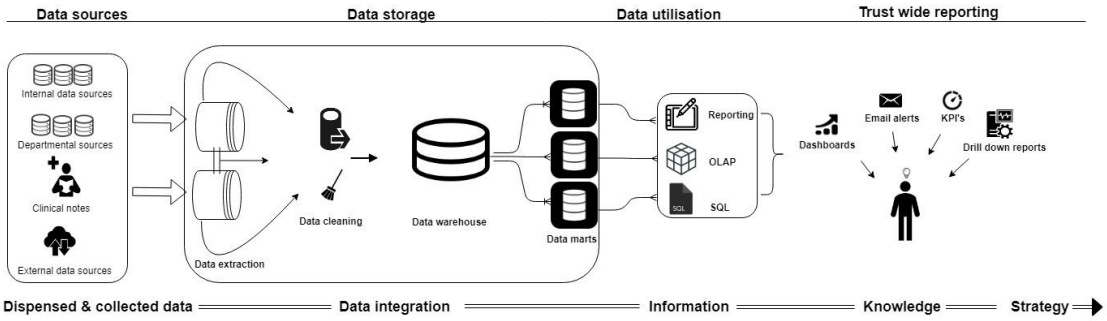


Figure 5.3 NHS Trust BI architecture (Created by Author)

5.5 NHS Clinical Portal

It is evident from Figure 5.1, (See appendix E for further breakdown), that this NHS trust offers extensive and highly complicated services from each of its CSU's between its seven hospitals and medical institutions. This highlights the data rich environment of the NHS and given the scope of its operations also illustrates the rationale behind collecting more and more data, which is aimed at understanding and improving the patient experience, whilst also reducing costs for the NHS. The supporting services which are evident across the Trust as highlighted in Appendix E includes the key organisational actors for this research, namely the 'Central Analysts' from the 'Performance and Informatics

Team'. Furthermore, it is evident through the strategic vision of this particular trust, that digitisation and consolidation is at the heart of its future aspirations. This became apparent through reviewing the Trusts 'Information and Technology Strategy 2020', which emphasised some of the key challenges faced by the trust.

Much of the challenges related to current ways of working, data sources and data quality. Accordingly, Figure 5.2, represents the vision of the trust in consolidating and centralising data emanating from variety of systems, through a proposed 'Clinical Portal' (CP). This clinical portal is a web-based system which generates a single, unified view of patient information. Given the scope and specialist services offered within this trust, the CP is tasked with consolidating patient information and results from different departments and specialities including other NHS organisations, thus offering an holistic view of a patient's care.

Therefore, the CP is highly beneficial, as it operates through a single log in, offers enhanced patient searching and has the potential to deliver a number of views of different patient information across multiple locations. In doing so, the CP combines systems, such as ICE, PACs, System One, to access and search patient information. It is evident that the trust has identified some challenges given the scope of operations and various data sources, therefore believe that by putting a centralised system in place which connects to 'Lorenzo' the patient information system, will help provide all members of staff an integrated view and thus a more reliable and robust representation of the data.

Therefore, this emphasises and maps out the Trust's drive towards digitisation. Importantly, various key themes emerge also emerge from this strategic vision. The trust envisages to drive digital transformation through 'Research and Intelligence', 'Clinical Patient Technologies' 'Resource and Asset Management', and 'Communication and Collaboration'. As such, the trust aims to leverage the data and technology by operating in a secure, yet flexible manner which allows NHS staff to use their mobile devices for their clinical

applications. Moreover, the trust also aims at consolidating their systems through the Clinical Portal, which will provide a single view of patient information and minimise, data quality issues. Hence, through proposing a data driven and consolidated view of the data, allows for a transparent and collaborative environment in which various organisational actors can effectively communication. While all these are essential dimensions connected to the digital transformation drive, importantly for the purposes of this research is the trusts emphasis on BI, and the need for such tools for decision-making purposes. Accordingly, the research identifies how the BI is currently being used across the trust.

Accordingly, this research also concerns how BI is used by various organisational actors. Although the architectural elements of the BI systems operated within the trust is not the focus, having an appreciation of the data streams and the processes in which the data is transformed for decision-making purposes is highly relevant, particularly for orienteering purposes.

5.6 Conclusions

This chapter provided a comprehensive breakdown of the case context, while still upholding confidentiality and anonymity of the NHS Trust. Through providing insights into the structure and functions of the case context enabled the researcher to justify this case selection, particularly given the increased use of BI within this NHS trust. Furthermore, this chapter also presented some insights into the technology roadmap for this particular trust, therefore providing further contextual details which are highly beneficial when developing the interview protocol.

6.0 Chapter 6: Analysis and Findings

6.1 Introduction

This chapter presents the key analysis and findings of this research. It presents evidence collected from interviews, notes from observations, and relevant discussions based upon documents. This chapter is structured to present the findings in the following order, the 'Social Pressures' emanating from BI use within healthcare settings. This theme presents insights into the contestations and conflicts between various organisational actors. This chapter also discusses in detail human factors during the 'Cognition' theme, which otherwise are largely overlooked in BI studies. These factors are shown to firstly affect the way in which BI is used, whilst also playing a key role in impacts power dynamics. The theme of 'Contextual complexity' offers insights into the environmental factors which also impact how BI is enacted by the organisational actors, which too has influence on the play out of power between managers and analysts. The chapter concludes with the dominant theme of 'Institutional Knowledge', which is a key factor in context of leveraging organisational influence. These themes were derived through the effective use of the conceptual framework developed and discussed in chapter 3, which allowed the researcher to provide an in-depth, rich account of BI use in the case context.

6.2 Social Pressures

The findings from this research revealed a prominent and recurrent phenomenon of 'Contestation' resulting from BI use. Specifically, it was apparent that BI use prompted various organisational stakeholders to engage in articulation and deliberation which often would lead to contestation between the stakeholders. These were seen to manifest across various situations and were the direct result of the way in which the BI tools were used, applied, and understood amongst individuals, belonging to specific groups. There was a disparity between functional ward managers, managers based in the directorates and the data analysts. A majority of the latter were based in the Central Performance and Informatics team, holding the view that they held a defined amount of power. This will be discussed further in section 6.2.1, where it will be highlighted that the types of skills possessed by these individual had a major role in this play out of power. In addition to the skills, the contestation and negotiation between stakeholders also played a major role. It is also worth highlighting that much of the contestations taking place between these organisational actors was as a result of their diverse skill sets and day-to-day

duties. While these differences were somewhat expected, the more interesting contestations and unexpected findings were the disputation and contentions which occurred within the same group, i.e. between the analysts themselves. These interesting insights will be elaborated upon in section 6.2.2. More generally, it is argued that the contestations resulting from BI use within the case contexts was a result of a disparity in skill sets (6.2.3), of using the tools and also contributed by personality styles which is explored further in section 6.3.4

6.2.1 Functional Managers and Analyst disparity – '*there could be a conflict, and it sometimes it's almost like an 'us and them'*

For the purposes of this research and as highlighted in the earlier sections the functional managers are referred to as 'service managers', 'operational managers', 'business managers', and the managers responsible for the day-to-day running of clinics, wards and other NHS services within the trust. While it is expected that the functional managers and analysts work in unity towards a shared goal and vision, the findings revealed that this relationship is not necessarily conflict-free and cordial. This is triggered further through the use of BI tools, as highlighted when a Central Analyst C.S, posits:

"I think you still have to provide the insight to what the data is doing, and our knowledge, but, you know within certain directorates, people [managers] ask for stuff which is pretty obvious? So yes, I think how you ask does influence how we will respond to requests as well."

It is evident that this analyst is discussing the extent to which they facilitate and provide additional insights into the data they offer to various departments. Here it can be deduced that the central analysts are able to pass judgement on the level of analytical skills of their end users, such as the functional managers, solely based on their line of questioning. This also reveals that when organisational actors from within the wards ask for something which is considered as 'obvious', this influences how the analysts perceive and respond to the question and more importantly the questioner. While this

denotes little from the context of power considerations, it certainly provides insights into the perceptions and attitudes of organisational actors, which are essential dynamics from an inter-departmental perspective. The heterogeneity between these groups of actors is further witnessed when another central analyst posits;

"I think sometimes there could be a conflict, and it sometimes is almost like an 'us and them', situation, like 'ooh what are they asking this for?', but you try to put that aside, as it's just working towards the common good isn't it? And, there might be some barriers, so we try to meet if time allows us to, but in back of your mind you have to think the patients are important and that's the most important thing."

The central analyst enunciates a clear distinction between themselves and the functional managers within the wards, interestingly in this instance the analyst highlights the 'us and them' as a way of describing their relationship, whilst also acknowledging the potential for conflict between both groups. The analyst immediately follows this up by suggesting that meetings may also occur between analysts and actors within the ward as a means to minimise conflict and refers to a general shared goal of serving patients as being worth all the effort. Again, this situation is driven by the perceptions the analysts have of the functional managers, based on questions posed by the latter which the analysts may not consider to be suitable or relevant.

However, the findings suggest that meetings between 'Central analysts' and 'Functional managers' were uncommon, infrequent and not feasible given the nature of their roles, targets and time constraints, which is further explored in 6.4.4. J.F, a Business Intelligence Officer, also acting as an analyst supports this by positing '*yes, it's rarely done through telephone conversations everything we do is pretty much through emails to be honest, it's the nature of the work, nobody has time!.'* Thus, from this it is apparent that the analysts rarely converse over the telephone and rely on email exchanges to deliberate with functional managers, therefore rendering physical interactions and meetings as highly unlikely. Senior Analyst, C.S further elaborates on the

impact of this by stating that through the use of email, things can be misunderstood and not correctly interpreted, particularly if you do not know the individuals personally: *'I would probably say that when it comes to analysts in the trust, we will know of them in some capacity, but the Service managers, Business managers potentially, they don't really know us, and I don't really know them, so when they contact you by email, it's quiet, it can be abrasive.'* Therefore, the nature of these interactions and the chosen means of communication can be considered as contributory factors in creating tension between the actors.

This was further witnessed when observing the central analysts within the Performance and Informatics department. Majority of the central analysts were working on a wide range of queries from across the trust, and the central analysts merely resorted to communicating through emails when there was the need to query or request further details from the operational managers who put in the original request. Further supporting the insights from the operational managers, it was observed that several central analysts were attempting to make sense of what one of the trust's service managers had requested, however given the distance and lack of interaction between the central analysts and the operational managers, it was proving difficult for the central analysts to decipher the request. However, given the target driven nature in which the central analysts operated, they agreed amongst themselves what the request 'most likely' would be used for and built a report accordingly.

When queried, the central analysts explained that they did not have the time nor the operational expertise to fully understand the rationale and motivations behind the request of the operational managers. This again is in line with the sentiments highlighted by the functional managers which led to the social pressures and dissonance between themselves and the central analysts.

In essence, the role of analysts is to provide insights which operational management can utilise for decision-making purposes. But much of the discussions indicate that while these interactions do occur, they are often

considered disputatious. In-house analyst, J.J provides further insights into the nature of exchanges between 'Service Managers' and 'Analysts' when referring to reports she generated for the spinal cord department:

'Errrrm, I think the more operational staff are, hmmmm (pause), if something doesn't look right, they are very quick to say no, that's not right!'

According to J.J, her experiences show that operational and functional managers, would question the data presented by the data analysts without spending time to acknowledge and understand the data. Therefore, this inadvertently leads to' back and forth discussions in which both parties attempt to disapprove one another, inevitably leading to a confrontational situation. The analyst further mentions: '*The conversation very rarely goes like this; ''well, how could it be like this?" It's more like, "I think, I think these just look wrong".. Whereas the sort of service manager kind of level, who have insights into the data would say "let's talk it through" and think well, if this is right, then why is it right. Does that make sense?'*

It is evident that the operational staff, would often doubt the data and show little interest in initiating a discussion relating to the data through their response to the data analysts. This again can be identified as another underlying issue which leads to tension between both groups of individuals. However, J.J highlights that service managers with more experience and understanding of the data would be more perceptible to the data and not as volatile towards it. As such, this stresses the role of expertise and skills in mediating and defusing a confrontational situation, which inadvertently can assist in narrowing the gap between both sets of actors. Adding to this further, Central Analyst, C.S explicitly refers to the us and them between the groups when *stating 'I suppose sometimes, I mean I don't know, whether that's historic them and us, we sometimes try to shorten that gap.. I think that plays a part why sometimes people are reluctant to ask is for help…'* Interestingly here, C.S provides further insights into why the service managers and operational staff may be reluctant and not willing to initiate a discussion with the analysts. She believes that historical undertones and obvious differences between managers and

analysts creates a situation whereby the functional managers do not feel comfortable to ask for more then what is originally requested, nor do they feel comfortable in delving into the technicalities surrounding the data. Therefore, the historic influences and the nuances held between both groups can be attributed to the lack of transparency and disparity which both parties, however exploring this further, it could be argued that the disinclination of managers to engage is due to their limited analytical skills, thus highlighting the influential role of expertise, which in this instance can be considered as an influential resource for the analysts.

Elaborating on these nuances and the perceptions, a Service Manager outlines that there is an inherent view within the NHS, particularly held by my data analysts that the service managers lack analytical skill sets and therefore the way in which the analysts communicate with service managers also reflects this. This is evident when A.H highlights: *'there tends to be this mentality particularly within the NHS, that service managers are not data friendly or they are, they lack data skills and that tends to be some type of a cliché, so when you are talking to data analysts, you always get that impression from them if.. Because I as a service manager also have some analytical insights and experiences and obviously skills, this allows me to make a lot of interpretations and even decisions without much assistance.'*

It is evident that the functional managers are viewed in a particular way, with much of this perception rooted in the fact that the data analysts assume the functional managers have inadequate skills to understand the data produced by them. However, it is evident through this service manager, that regardless of her operational role, this does not imply an absence of analytical skills. It can be argued that such informal dynamics within the organisation can create tension and lead to contestations. Despite the fact that analysts may deem this appropriate based on their preconceptions and take such an approach with good intentions, not to overwhelm what they perceive to be non-technical managers, those functional managers, such as A.H who do possess analytical skills may feel they spoken to in a superficial and overly simplified manner. This is this is strongly communicated by A.S: *'So I do feel there is that*

stereotype that service managers tend to be more about managing things as opposed to understanding the data.'. This form of categorisation by data analysts is underpinned by not only how they expect managers to interpret data, but is also as a result of how the functional managers ask questions. For instance, J.J posits: *'I think, yes there is quite a lot of that. I think I, they might ask a question and it's quite clear that's not what they want. The answer to what they request isn't going to answer actually what they want to know.'* Similarly, S.K, business analyst highlights: *'Yes I know now know what people usually ask questions about, even though it's never the right question, but I can anticipate what people are wanting to know'.*

These examples highlight how the functional managers may require a particular piece of information, yet fail to articulate this effectively to the analysts. Consequently, the analysts argue the way in which functional managers request information reveals their level of analytical skill set. This is further witnessed when Central Analyst S.G posits: *'it's generally straightforward, the way in which the requester (managers) requests, shows a lot about their data proficiency, we have to then respond according to that'.* Thus, the extent to which functional managers are able to identify key variables and key pieces of information supposedly reveals their analytical prowess, or a lack of it.

While it has been highlighted that service managers may not fully understand the data and what the data is telling them, conversely it was also evident through discussing what happens within the departments that the analysts were also not fully informed and therefore lacked some of the contextual insights. This was evident when the analyst highlighted, J.F; "*I'm not sure what the 52 week target is itself, but it is just something that we have to look at just to make sure they don't breach that date, but again I'll let somebody else explain that."* This indicates that although the data analysts may have the ability to pull together relevant data and also interpret what the data is telling them, they may not necessarily have an understanding of what this may mean in relation to some of the wider targets or the wider implications of the data. Similar sentiments were also shared by General manager, J.W, who

repeatedly emphasised the importance of knowing what is actually happening in the wards as opposed to solely relying on the data; *'so, it's, it's about trying to nuance some of the black and white of the numbers against, experience and knowledge of, you know because, the clinicians and the admin and nursing team have really, in depth gut feeling, that I suppose that they can bring into that as well'*.

While the findings unravel many insights regarding the 'gut feeling' of various actors in section 6.3.1, it is generally understood from this that the general manager appreciates the data but regards the knowledge and experience from various actors with the aim of the actual setting, just as important. This is further highlighted when service manager, A.H states; *'For example, like a number of patients on the waiting list, I can have a conversation about whether that's more or less, or whether that feels like, but it is a number at the end of the day. Isn't it?'* While A.H has relevant data analytics experience, she is referring to the numbers as 'merely numbers' and that further insights can be gleaned through conversations, something the numbers and analysts are unable to provide. While it is the numbers that help initiate these conversations, the service managers reveal the increased importance of the latter, when making decisions.

It this therefore evident that much of the contestations between both groups are as a result of diverging skill sets this is discussed further in section 6.2.3, nonetheless, while the functional managers may lack the skills to analyse the data, the central data analysts also lacks contextual understanding and localised knowledge. This was picked up also by Deputy Service Manager, R.G, who acknowledges the divide between themselves and the analysts and believes this can be overcome through each set of actors understanding a little more of each other's world;

'So I believe operational managers need to speak a little bit of business intelligence, and I think the business analysts need to speak little more of the operational manager. And I think the further away those two groups are

located, part of it is physical and part of it is hierarchy and the structure of the organisation, the more 'no man's land' you get in the middle..'

It is therefore, this 'no man's land' where contestations, disagreements and incongruities occur, while it is argued that the disparity in differences in their skill sets was a resulting factor which contributes to the contestations that occur between service managers and the data analysts. However, from within the context of power considerations, it can be argued that the ability to overcome disagreements and the ability to negotiate your reasoning and point of view to the extent that it is then used for decision-making purposes is a sign of having influence and authority from within the decision-making context. However, based on what has been discussed, it is evident that limited articulation occurs, particularly between the central analysts and the service managers. So, in this regard it can be argued that while the analysts possess the analytical skill sets, the decision-making power and the ability to make a decision remains with the functional managers, regardless of whether they operationalise the data endorsed by the data analysts. As such, although tensions are raised based on skills and contextual details, it is argued that the functional managers retain and possess decision-making influence.

6.2.2 Analyst Incongruence – *'Our titles maybe the same, but our approach differs'*

Interestingly, aside from the functional manager and analysts, analysts were seen to have contestations between themselves, whereby they held different views, operated in a disparate manner, and did not refrain from criticising one another. Much of the 'tension', between data analysts was between the 'in-house analysts', embedded within departments and wards across the NHS and the 'Central analysts' that were part of the Performance and Informatics team who were geographically located away in the corporate office and not based in any directorate and ward. The in-house analysts were considerably less in number in comparison to the central analysts and were sporadically located across the trust.

It was the opinion of the in-house analysts that the central analysts lacked contextual details, were not aware of how the wards were operated and thus did not have 'true' understanding of the data and were unable to correctly interpret the data that they were generating through the BI tools. On the contrary, there was a consensus, barring a handful of central analysts, that the role of analysts was merely to provide actionable data for decision making purposes by the functional managers. As such, there was no issue of skills as both central and in-house analysts had the relevant skill sets to interpret and manipulate the data, however the disparity in this instance was more in relation to the localised insights which are discussed in a lot more detail in section 6.4.

Deputy service manager, R.G emphasised the role of mutual understanding and how the functional managers and the analysts could overcome their differences by firstly understanding more of each other's roles, responsibilities, skills and more importantly having the prudence to explore things from each other's perspectives. While this is an appropriate recommendation, it is somewhat idealistic and very difficult for this cross over to occur, given the nature of the NHS as discussed in more detail in section 6.4. However, it was evident from within the discussions that contestations not only occur between the functional managers and analysts, but also occur between analysts themselves. While this was not expected in the findings, it was apparent that these contestations were frequent and deep-rooted.

Here, R.G was referring to the ability of having a cross over and reducing the gap between the functional managers and data analysts. However, it is apparent that the analysts embedded within the care groups and departments were able to exercise not only analytical insights but also localised knowledge when making providing information for decision-making purposes.

'I don't know if you're fond of motorsport, you've got drivers and engineers speak a different language. The driver says, I've got far too much or too much understeer in the car to power down quick enough, or else the rear end will be going out of the corner. The engineer has to then translate that into how do I adjust the suspension and the brake balance to stop that from happening..

Sometimes you need somebody to translate a crossover between them, because they have a different experience and they are speaking a different language, but they are trying to get to the same thing. So it's about how you get that mutual understanding.'

This analogy exemplifies the challenges associated with collaborative working between diverse actors. The nature of contestations between the analysts themselves were also based on their divergent, conflicting perspectives resulting from their disposition within the NHS trusts. The central analysts were seen to differ considerably to the in-house analysts due to several factors. Firstly, the central analysts are part of the Performance and Information team, who are closely aligned to Corporate Services, operating remotely across various department. Conversely, embedded within the operational setting, the in-house analysts are regarded as a valued asset for directorates. Therefore, the latter have the insights into not just how operations are managed but are also readily available by all the operational actors within the ward such as managers, clinicians and admin teams, which not only widens their breadth of experience, but also enhances their influence within the wards. Therefore, this resulted in the in-house analysts often questioning the methodology and approach taken by the central analysts, thus leading to a rise in tensions, based on either the provenance of data, or the inability of the central analysts of taking into consideration pertinent factors that influenced the decisions made in the wards. Service Manager, A.H emphasises this in the following:

'For one of my consultants wants to know how many newly diagnosed diabetes patients got admitted for A&E last year, I could go down the corridor now and have a joint dialogue about what I wanted, but if I was to send it off, I would wonder whether or not it is going to come back. My local analyst is good, it is that sort of local knowledge, understanding and influence whereas on the other hand the central analysts, well they are a corporate resource and they need to respond to things that are famous for everybody I suppose so, there is lots of national reporting that they do on our behalf with no, we don't need to'

This substantiates the fact that the service manager favours the localised insights from an in-house analyst, as opposed to the central analysts., A.H refers to how from a broader perspective, the central analysts are a corporate resource and their focus is on what is current and 'famous', therefore exert time and effort reporting on what is nationally deemed as important and critical, which may not necessarily be the priority from within the ward. Whereas conversely, the in-house analyst is able to facilitate with more tailored and relevant queries that have practical implications for the ward, hence considered a valuable resource within the operational settings. Accordingly, the central analysts are seen as somewhat irrelevant when compared to in-house analysts. By this, it can be deduced that while the service manager may require the service of both types of analysts, the in-house analyst may be more influential given how they are perceived by the service managers as opposed to the central, corporate analysts.

From the perspective of a central analyst, C.S emphasises this and concurs with the service manager, A.H, when she highlights:

'*The in-house analysts have more of an insight into how they service works, and I think we offer such a broad range.. you know we do not necessarily specialise in, where I have worked before I was the A&E analyst and I just did the A&E data and I was, I felt really comfortable with all of that, whereas here we tend to, and so any requests so, you know it's very good in that we have flexibility when people are off and everything, but we don't necessarily get that expertise that you might get out in the directorate's…'.*

Interestingly, this analyst has worked in both contexts, as an in-house analyst within a care group and as a corporate, central analyst in her current role. She highlights the ability of having that specialised, in-depth knowledge and highlights how she was 'really comfortable' in her role, which refers to her ability in producing data for and liaising with the operational staff. Although her current role as central analyst allows her to understand some of the operations on a more broader scope, there are palpable limitations, as the expertise and contextual knowledge is missing when operating as an analyst away from the

given environment. This is further emphasised when C.S mentions: *'I do feel that we are in an ivory tower here, we have moved so far from, well I very rarely now go out of the office over to the main sites, but it's not a frequent thing for us to go out and visit the services and the CCG'. When I worked in Leeds, where I was working within the A&E department, I would go across to their weekly meeting where there was often quite heated debates between the ED (emergency department) clinicians and the AMU (Acute Medical Unit) clinicians, so you are able to contribute to that discussion because you know the context and the data better then both sets of clinicians.'*

The analyst highlights that physically being away from the services is a hindrance, referring to this through the description of an 'ivory tower'. However more interestingly, she highlights that in her previous role, she would not only work in the department but would also be involved in their weekly meetings. Through this, she was able to interact with various actors within the wards and would be able to contribute meaningful insights due to her data expertise, and her localised insights. From within the context of power dynamics, she highlights at that by being in the context and being involved within the weekly meetings, she is able to also contribute towards what she refers to as '*heated debates'.* This is of relevance in the context of this research, while it is understood that central analysts do have discussions with the functional managers, although this is often limited to several email exchanges, due to them not physically being in the environment, their influence is limited. As such, the analysts are unable to fully exploit their expertise. On the contrary, by being in that environment, by knowing the staff and understanding the contextual details, the in-house data analyst is able to influence more decisions and outcomes.

Further insights into the role of context in impacting power considerations as a result of BI use is extensively discussed in section 6.5, however, when putting into perspective the difference between her role as an in-house analyst and central analyst, C.S mentions: *'being in the environment is good for insights, it's them contextual details it give you which are not readily available through seeing the data if that makes sense?'* The insights that C.S was able

to absorb by being in the ward would not be evident through reports and through solely using the data. By supplementing the local environment and its dynamics with the data, made her more valuable as an in-house analyst.

The disparity and lack of cohesion between functional managers and central analysts is further emphasised when C.S posits: *'they were a bit more open with requesting data, but here people don't necessarily get to know you or sometimes they feel a bit silly asking questions and things like that but for example when I worked in Leeds, people would just ask, I'm being silly but have a look at this' and yes, I really quite enjoying that it was really fast-paced and everything.',* Building upon the earlier discussions, C.S feels that the relationship between herself as analyst and a functional manager is paramount, particularly for functional managers that lacked analytical skills and would require assistance on routine queries.

Therefore, communication and relationship building can be seen as a key factor in ensuring successful BI use. Adding to the sentiments of C.S, central analyst J.R emphasises the lack of interactions that take place between themselves, the analysts and the functional managers: '*there is not a lot of communication between us and the care groups to be honest, it's just really us sending them the data, if there is anything they think is not right, we'll try and look into it by obviously rerunning the data just to make sure there's nothing wrong with it'.* It is evident that when comparing how the analysts deal with functional manager queries, the central analysts are heavily focused in the detail of the data, and thus lack communication and can be considered less flexible than the in-house analysts.

J.J, whom also operates from a local context as business analyst within a ward highlights: '*I think if I hadn't been based in that environment, then it's really hard to imagine can you do a report on this? when you've been in that environment for a while, you get a good feel for whether they are asking the question that they want answering.'* This is another indication that successful use of BI at analyst level requires the ability to anticipate what the functional managers may want to know, and this is possible through working in the ward,

as the in-house analyst do, in spite of how limited the analytical skill sets of the functional manager may be.

The disparity between central analyst and in-house analysts was highlighted on many occasions, J.J explicitly draws upon the differences when mentioning:

'It'd be good to ask someone who, firstly worked in an actual environment and then has worked as an analyst centrally away from the environment, that would be a good reflection.. You'll definitely the analyst who has worked in their former settings i.e. within an environment would absolutely struggle to adjust to working geographically away from an environment that's how I would imagine it personally.'

Resonating with C.S, J.J also provides insights into the differing nature of work and the difficulty in adjusting to the role of central analyst after having exposure as an in-house analyst within a care group. Therefore, through this it is obvious that in addition to the functional managers, the in-house analysts also have an uneasy and uncomfortable relationship with the central analysts, which is mainly underpinned by their ability to understand the local contexts better. J.J refers to situations that can get missed and overlooked centrally, due to a limited understanding of operational processes within the wards. From an operational context, particularly from the perspective of managers, it is argued that this oversight has enormous implications for their operations, as information that fails to consider the 'entire picture' may be misleading and result in decisions being made on false, incomplete information.

It was evident that the in-house analysts are able to win the support of the functional managers by presenting them with more creative and realistic analysis which are appropriate, fit for purpose and aligned with the context of the operations of the wards. It is for this reason that the in-house analysts are seen as their prized asset within the wards, as also highlighted by service manager, A.H*: 'You can ask information services to build your report, but they've obviously got a day job, and a backlog of things to do. So we've got, we're really fortunate in this care group that we've got the capabilities for people to do that'*

While these sentiments offer insights into the disparate nature of these roles, other organisational actors extensively discussed the dissonance between the local and central analysts as a result of their divergent perspectives. For instance, senior Improvement manager P.G also weighed in on this discussion by emphasising his relationship with one of the senior central analysts:

'I would say, there's been times where we have disagreed, and ultimately, what that boils down to is he.. is (pause).. He understands the data a lot, But what he doesn't have as much knowledge as people like me and others in the services, like the reality of processes on the ground. And, not all of that is reflected in the data. The data is pretty right, like 90% right, but there will be times, where we have clashed a bit before , that comes from assumptions that can be made about individual behaviour based in data, like 'that surgeon is dead slow', or this one is like that, and actually when you do work with the team on the ground, there is something underlying that that is, is sort of usually incorrect'

Here, the improvement manager highlights that the analysts are extremely important and that they do serve a purpose and often they are able to provide meaningful insights which are embedded in the data. However, P.G mentions that one of the central analyst and him often do disagree due to the analyst not having the local knowledge, yet make assumptions based on what the data is supposedly suggesting. This also highlights another reason as to why there may be conflict and tensions between various organisational actors and the analysts, due to the central analysts from their objective, data driven disposition, interpreting data without supplementing what is happening in the environment.

This was also witnessed when R.J provided bed availability and occupancy reports which were produced centrally by the analysts. When reviewing the reports, it was evident that R.J was able to pick out a number of analyses within the report which were not reflective of the actual situation within the wards. For instance, the reports suggested that there were a lack of beds available, however R.J highlighted that the reports did not reflect patients who

were internally transferred between various wards for additional checks, thus freeing up beds in certain specialities. R.J was confident in stating that more beds were in fact available and that the central analysts were not able to predict the likelihood of the patients duration of stay due to them not having the operational, local knowledge. Thus, the report was highlighted extensively by R.J, who stated that these analyses were not accurate and a true reflection.

This was also highlighted by another manager, J.A, who was also responsible for managing clinicians, operational staff and in general, daily operations within a busy ward. She highlights that while the data is extremely important, it requires the local insight to be meaningful. This can be seen in the following discussion: *'yes, I mean imagine if we had a day to switch off? How would we be able to manage our staff our operations and drive change? But what I would say is, whilst the data provides the black and white, the people and the local intuition gives it the colour.'*

From this we understand that the operational managers do appreciate the role of data however in order for it to be meaningful and relevant to the context, there is a need for the local insights to be supplemented with that data. However as also discussed in section 6.2.3, the lack of analytical skills of the functional managers makes it difficult for them to supplement the local knowledge and intuition to the data, particularly when the data is opposing their intuitive, localised knowledge and insights. Thus, when it comes to analyst types, the functional managers who have experience and interactions with both, perceive more benefit from the in-house analysts as opposed to the central analysts, nonetheless, this does not imply that the in-house analysts and the functional managers do not dispute, however due to the influence and capabilities of the in-house analysts, this occurs less frequently.

6.2.3 Skills Disparity – *'It's not about data, it's about skills and being able to interpret the data'*

An important factor underpinning the contestations between the various groups and organisational actors were underpinned by skills disparity. This was more evident and prominent between the functional managers and data analysts. The ability to not only provide data but also interpret and make decisions on the back of data produced by BI tools was not consistent and certainly not similar for functional managers and data analysts. Therefore, it was understandable that managers with limited analytical skill sets were drawn into more contestations and disagreements with analysts. This was either explicitly expressed by both functional managers and analysts, or done so more subtly as will be discussed in the coming section.

Additionally, with the organisation strategising towards a paperless NHS, whereby more data is collected and relied upon, this can prove to be unsettling for functional managers, who lack the skills to make appropriate use of the data. This was highlighted by the service manager, A.H:

'Given the capabilities within this organisation to supply data and looking at data, you are, I think, I think we work in a culture where, you are expected to work with data, and if you don't, you, you are going to be heading into some difficult conversations.'

It is evident from here that the organisational culture demands that not just the analysts, but also decision-making managers are well acquainted with analysing data and interpreting the data, it's implications and interpretations. Therefore, this creates a situation whereby the managers particularly those who lack analytical skills rely heavily upon the skill-set and clarifications of the data analysts. As such, this can be seen as having implications on the power dynamics within the organisation, particularly given that the in-house analysts report directly to the functional managers and are responsible to them within the organisational hierarchy. However, now the analysts due to their skills are

seen as having a certain degree of influence, regardless of their lack of authority. This is further emphasised by A.H, when she highlights:

Ironically, whether you believe the data or not, you will use it.. You go to your performance meeting, and somebody will say, have you seen this? If you haven't seen it, you, you are already lost, whereas if you have seen it, we will be like 'yes have seen it, I've done some digging, I know that that actually means this and that… And have decided not to use it' then it's a much more, you can have a more, confident conversation I suppose..'

It is evident from this that, the use of data and showcasing oneself as being data friendly and data competent is imperative, particularly during meetings where there are many actors who expect you to know the data and highlight analytical competencies. This was evident on various occasions and is discussed in more detail in section 6.3.5, which explores the importance of data within meetings and business cases. Similarly, L.B highlights the data driven nature of collaborative meetings, when sharing her experiences about the elective care working group. She highlights the emphasis placed on data in such meetings, however also discusses the importance of having the courage to admit if one has limited analytical skills. This is highlighted in the following:

'It's a meeting, where all of my types, ops directors and other managers attend… it's very very data driven. I always say I don't have no idea what you're talking about', so I am asking the questions which most of the other people think they know the answer to, but won't ask. I think it's having the courage, it's about the courage of putting yourself out there to say what? Because we all sit there agreeing, but I will openly say it if I don't know where to get the data from'

Many interesting elements can be deduced from this excerpt. L.B acknowledges the data driven focus of the meetings she regularly attends and supporting the sentiments of the service manager, A.H, she also highlights how other managers are reluctant to openly question the data or reveal their inability to interpret and understand the data, as such prefer to 'go with the

flow'. This links to the findings discussed earlier, which revealed the expectations placed on functional managers to understand and interpret the data. In this instance however, it was evident that L.B had the confidence to question the data and to openly mention that she was not too close to the details or the analytical skills that others supposedly had. It is possible that she was able to raise this and had the self-confidence to do so due to her position, i.e. as Associate Director of Operations, thus emphasising the role of hierarchal influence. It can also be argued that lower ranking functional managers and operational managers may be more reluctant to be so open and honest in this regard.

This overarching and rather uncomfortable situation for the functional managers was also brought to light when Improvement Manager P.G states: *'I did my own, I was less experienced, so it was a bit random what I did. Then I would also, I guess, often it felt like you were almost making it up as you went along. And the risks of that are, you are forming decisions and informing others based on, stuff that might not necessarily be true.'* Therefore, given the rigorous data culture and the expectations of the functional managers, it is clear that managers take it upon themselves to interpret the data and make decisions based on their own analysis, although their skills may not qualify them to do so, as in this instance highlighted by P.G. This then may lead to incorrect actions and decisions and even disputation, resulting from the incorrect understanding and interpretation of the analysed data.

Conversely, it was evident that not all functional managers felt the need to justify their level of analytical skills, nor felt the need to actively engage with the data. For instance, business manager, S.C, highlights: *'It's like the heads of schools are not always schoolteachers, and that doesn't necessarily make them have the right qualifications, but it also doesn't mean that they've got the wrong qualifications either?'* As a justification for running several wards without having analytical skill sets, S.C argues that it is not a requirement for her as a manager who managers people, including more analytical members of staff, to have an analytics background. She uses the analogy of head teachers, who

may not be teachers nor have any experience of teaching yet have the ability to operate and run schools very successfully.

When exploring documentation, particularly communication exchanges through email between analysts and functional managers also revealed this skills disparity further and supported the sentiments highlighted by the organisational actors. For instance, one particular email conversation thread was a discussion between a functional manager and analyst, which revealed the lack of knowledge the functional manager had regarding BI data, highlighted through the managers inability to interpret the results of a BI report despite numerous attempts within the email exchanges by the analyst to explain them. Eventually, the functional managers explicitly requested the analyst to explain what the implications of the results were as a means to put the conversation to an end.

Skill sets of the staff evidently varied, and it is important to acknowledge this when attempting to understand those who influence the decision-making process. A.H tries to group this according to those who work directly within her ward:

'I think you could say, now that the in-house analyst has insights into the operational side and also the performance of the clinicians and doctors, they all have to befriend him! Otherwise clinicians can't get away with pinning delays or underperformance on their procedures, because the analysts knows it all'

It is evident that the analysts is able to exert a certain degree of influence as they have analytical skills to monitor performance, while also being aware of contextual details relating to expected time for procedures. Therefore, having influence on the clinicians also. Given the data driven nature of the NHS and the emphasis on data driven decision-making, it seems that organisational actors compare themselves to others when it comes to data proficiency, as the diverse set of actors within the wards have diverging skill sets, which can lead to numerous and inconsistent outcomes.

M.B, Business Intelligence Officer adds to this by highlighting: '*yes definitely, not many people are confident to work with the data. So having that expertise does make you feel a lot more valued within the department as a whole, because you are able to then confirm whether or not the orders are seeing the data in the right way or not.'*

An example of how this divergence is mediated can be seen when one of the operational directors was discussing her relationship with her in-house analyst within her wards. L.B mentioned how her analyst had exceptional analytical skills which allowed him to manipulate and transform data for decision-making purposes. However, it was clear that while this skill set was a valuable asset, it also, according to the operational director has its drawbacks. This was seen when L.B states; *'R.B, his brain works very quickly, he's very analytical, I would argue he, he rushes some stuff, And he'll knock up a graph, I'll be like yes, but you haven't put any titles on it?.. So I actually don't know what it's telling me, and he will say yes sorry, and he will, so do you know what you mean? You would put the extra 5% on it, and then I would be like now I get it.'*

Due to his skills, he is able to churn out many reports with limited effort and in a short period of time, however much of this is often amended upon the request of more functional operational managers and senior managers such as L.B. Now, it can be argued that this way of working is a direct result of the target driven environment in which analysts operate, however it is clear that less technical and analytical actors, such as L.B require more subtle details to help contextualise the findings with simple additions such as headings and labels. This iterative process, whereby the functional manager is able to provide further suggestions to improve the data being produced by the analysts is key, yet such flexibility would not be possible with central analysts.

Similarly, C.S highlights: *'I would say it's a mix, some managers out there who can make their own SQL's, but others don't know so will need everything explaining, line by line!'.*

This again highlights the varied skill sets of operational managers, while some may be operational and analytical others are not so much. L.B further

highlights her lack of analytical skills by making a distinction between herself and other analysts within the organisation: '*they are clever people who know how to get stuff out of the sausage machine, they laugh at me, because everything is sausage machine, b*ecause *you put stuffing, and something happens and then you pull stuff out, so yes we have a lot of sausage machines (laughs)'* L.B in jest, refers to analytical tools and its ability to transform data into reports as a 'sausage machine', thus acknowledging her limited analytical skills. But she is able to justify this through the way in which she projects the importance of her own skills: *it's always a conversation. It might be a challenging conversation, because I recognise my style could be challenging for their professional… So I, mostly would not understand the information in the first place, because my brain doesn't work that way, but through questioning everything, I get there and bring them along in the journey.'*

Here, L.B highlights that she is not only learning through questioning the analysts regarding their data, but she is also benefiting the analysts by helping them gain a better insight into non-analytical reasoning and how to tailor reports towards non-technical end-users. Supporting this, an examination of documents made available to this researcher also revealed that various members of the operational team had requested analytics training on multiple occasions. However, it was interesting to note that this training was for the same workshops, highlight that either the operational staff, including managers required regular reminders as attending once was not sufficient, or that the trust did not have a structured training programme to develop non-technical staff. When probing this, J.W posited:

'In all honestly, it become a ticking exercise, to at least say you've tried if you ever get asked why you don't understand the BI data after years of it being in operation'

The disparity in skills was widely expressed, both by the functional managers and analysts. P.S, the senior analyst from the Performance and Information team highlighted this when mentioning: *'The difficult bit is people say they want stuff, but when they have it you realise they don't have the time to use it, or*

they don't have the skills and on top of that, while they don't have knowledge either… They have no idea if it's right or not.. I mean it's awful when you give it (analysis) out to somebody, and they can't even tell you whether is right or wrong.'

Here, P.S is emphasising what is discussed previously, in relation to the lack of skills across the departments when it comes to interpreting and analysing data from graphs and reports. To the extent that the functional staff are unable to identify, whether what they receive from the analysts is correct or incorrect. This further highlights the disparity in skills and how this may hinder and breakdown meaningful communication between various actors. In addition to this, findings also reveal that managers may also not be aware of the capabilities of analysts and the level of information that they can provide.

Interestingly, much of the contestations that were highlighted were a result of the divergent roles, responsibilities and skill sets across the functional management and data analytics teams. As also highlighted in early discussions within this section, the skills disparity and gap between managers and analysts to understand and interpret data was a re-occurring theme from within the narratives. For instance, deputy service manager, R.G emphasised this from a skills viewpoint. He posits:

'If I'm being honest, operational managers generally don't see things from a data analyst point of view. A - I don't have the knowledge, and B - I don't have the time, I'm not a programmer, and not employed to do that I'm employed to be a manager, and make decisions. Therefore, I rely on other people to provide me the information, which is not always, A - a in a timely fashion that I need it and B - the format and quality that I need it. And often I spent time manipulating and playing around with the data going back and asking secondary questions because I have not got what I needed first.'

Again, discussions around the inability to see things from each other's perspectives and the underlying factor that both sets of actors share different skill sets is evident here. R.G, highlights that as a service manager he does

not have the skills to access and pull the data which then requires him to rely on others, thus highlighting the lack of analytical skills. On the other hand, he also highlights that he has to go back to the analysts due to the lack of quality and format of the data provided. Here it is evident that he is referring to the lack of quality in terms of applicability and relevance to the context therefore he resorts to going back with further questions which leads to an iterative process which is also time-consuming. Nonetheless, this process is more time-effective and iterative with the in-house analysts.

The skills disparity between the functional managers and analysts was expected, given their differing role and duties. However, it was also evident between the analysts themselves. R.L, in-house analyst highlights *'while we do the same things, the way we do them differs considerably. While they may be working off jobs list, I may be working off specific requirements and actual issues.. So our skill sets are developing at different paces as a result of this'.* Here, R.L expresses that while he shares similar attributes to the central analysts, in terms of their job description, he feels his involvement at a more microlevel within wards enables him to develop other skills, which the central analysts may not necessarily be developing. Additionally, R.L also highlights the skills required in coding*: 'it's only ever as good as, you are relying on people putting the correct code, you know if it's thousand with thousands of records may be, inevitably.. There could be human errors'.*

Similarly, P.S also highlights the different ways in which analysts may code the data: '*it's basically a mixture of experience and precaution really. I think, if data is not consistent you are going to get problems. Whatever, and I there is a zillion ways to write the same query. So I could go out there and give them all a query and they could all come back with a different SQL, they all will probably get the same answer, hopefully fingers crossed (laughs).'* Therefore, the ability to code correctly depends on not just the data, but also the experience and creativity of the analysts, which can differ considerably from analyst to analyst, particularly from central analysts to in-house analysts, who were exposed to differing contexts, situations and insights.

Through the narratives it was obvious that there were deep-rooted issues resulting from the diverging skill sets of organisational actors working in close proximity, such as decision-making managers and analysts. There was also a sense of reluctance on the part of some of the central analysts when discussing their experiences with the service managers evident through statements such as; S.G: *'Hmmmmm… I could be stitching them up here couldn't I really?', P.G; 'I don't want to come across as being harsh'.* S.G, elaborates by stating;

'Errrm.. I think it's widely accepted in the trust that the analytical levels of service managers varies from department to department,. So some might be better at managing a department, but when it comes to analysing data they may not be quite so, so good. There is a wide variety of ability specific to analyse data, so they're all good service managers but they do vary a lot. Some will be colleagues within that department that work with the service manager who might have more of an analytical background, to put into plain English what they are seeing in the data rather than the service managers themselves…'

S.G emphasises inconsistencies and variances in the analytical skills across the departments, and how this requires people within the wards and departments to up-skill themselves in order to make sense of the data. While he refers to the in-house data analysts who may be supporting service managers in their interpretation of the data, this interpretation may vastly differ to that of the central analysts who develop and produce the data in the first instance.

The synergy and expectations of analysts within the services is also worth noting, particularly given their analytical disposition and the fast-paced nature of operations that occur within the directorates. Clinical analyst S.P, highlights this when he discusses:

'I think there is an internal conflict for analysts, particularly those who are embedded within wards and services. Due to the operational focus in the wards, they'll find that their background and analytical skills are very different

to their operational peers. So whilst everyone else is firefighting and solving business problems, you can end up finding yourself doing a lot of stuff, which may not have immediate or direct impact'

S.P who was originally part of the central team raised some interesting points regarding how his analytical role fits into an operational environment. He argues that when you are directly contributing towards a solution or providing information that can help with a particular business problem, you feel your worth, but otherwise, you begin questioning what impact you're bringing to the ward. Therefore, psychologically, the in-house analyst is more pedantic, more committed and more driven to provide solutions, to learn more about their settings, to the extent that on occasions they become more conversant of operational intricacies than some other functional managers. Therefore, due to analysts being of a different disposition, in an operational environment indirectly benefits them, allowing them to influence various aspects. Conversely, he mentions that when he was in the central team, and colleagues were doing the same thing, i.e., churning reports out, there was no real feeling of accomplishment or achievement.

Therefore, it is evident that managers and analysts, and the analysts between themselves have specialist knowledge and specific skillsets. As in any organisation, the underlying success of organisations is in its ability to bring together and disseminate knowledge between diverse groups of actors and across various. However due to the emphasis of data and the target driven nature of operations within the wards, the analytical skills gap in skill sets between the functional managers and analysts particularly is magnified, which either leads to misinterpretation, contestation and tensions between these actors.

6.2.4 Data Vs Intelligence (or Transforming) – *'we offer data.. we don't really offer analysis, we don't offer insights'*

Another common discussion related around the impact that the BI data was able to achieve. This code, explored the 'so what?' concerning the data, which

were the sentiments frequently expressed by the functional managers. This code therefore critically analyses how the functional managers perceived the impact of BI data and thus explains the importance given to its use. It was the belief of some of the functional managers that the overemphasis on data was not necessary, whereby they would question the value obtained from collecting this data. These can be seen in some of the following statements:

Business manager, S.C refers to this when she highlights that in addition to the data, often the human element is overlooked particularly by the 'policymakers', this argument again links back to whether the data is providing intelligence, and to what extent that intelligence is having an impact on operations. She further states: *'Besides BI, there is a lot of people intelligence, or people side of it. So for example, in our department, it's very hard to bring in somebody periodically if we have staff shortages, to be able to pick up the role, there are a lot of standard operating procedures, there are a lot of SOP proven tasks, there is, there is a lot of inherited intelligence, learned intelligence I should say. Which the data could never give you.'* The statement here clearly highlights how data is perceived by the business manager, as she compares the human intelligence which her staff possess against the supposed intelligence on offer from the data.

Enterprise Architect, S.S, similarly was very vocal when explaining the impact, the data was having on operations and services within the NHS trust. He argued that there was an obsession of collecting data, with little value. 'And basically, we offer data, we offer reports we don't really offer analysis, we don't offer insights.' While S.S is not in a functional manager's role, he also resonates with what many functional managers have outlined in regard to the abundance of data, plethora of reports, yet limited practical implications. He goes on further to say: *'But, we've got it all, we've had it all, and we got it all, what change was enabled off the back of that insight???!!! and if it wasn't, why not, what has it got to do with, it's got to do with culture? What makes, why is it that we don't have action based on intelligence!'* More specifically here, he suggests that as an organisation, they have the data, the tools, the people in the roles to deliver it, but limited changes are being made off the back of all of

this. He argues that perhaps it has to do with culture, again referring to the over-abundance of data, the strategic vision of the organisation, moving towards a paperless environment and the organisational structure.

Comparable to the sentiments previously highlighted by L.B, S.S also homes in on the fact that the data is heavily based on historic events and the organisation is yet to commit to more advanced forms of analytics which will allow for more precise, timely and effective predictive analytics. This can be seen when he states: '*we have way too much data, no one has a plan for how the trust should be leveraging the data, we have a lot of aspiration about visualisations, analytics, but at the moment, the data is watching them crash, but it's watching them crash before a nurse notices them.. there are very very small pockets of total insight, that jumps you beyond data and information it's jumped beyond analytics, you're now into personalised insight per individual.. To change care.*'

Service manager for performance, J.B also alludes to the need for the trust to move towards predictive analytics when he rhetorically asks: *'why can't we? I mean with all this data, why can't we map the weather against what A&E might look like for the trust? Can we factor variables like supermarkets do, to look forward 5 days?'*

It is evident from these insights that the data is not seen as delivering value, or necessarily driving change. While the managers acknowledge their ability as an organisation to collect the data, they also recognise more can be done with the data to achieve real impact. Therefore, opinions expressed by the functional managers indicated that the NHS has created and continues to promote a culture around data, while also strategizing ahead through being data-driven. However, there is a lack of standardisation across the trust in how this should and must be managed, as such, this culture has indirectly created a situation whereby much emphasis is placed on being data driven, however with little insights or impact being gleaned from this.

Service manager, N.A, opens up further on this issue as states:

'We tend to use the data much more the opposite way to, we know we need to do something, we want you to do it, have to shout till you're blue in the face and use as much data as we can possibly get our hands on to, to prove something, and that data is almost exclusively quantitative and very rarely qualitative.. Qualitative data is not classed as science, so, people use words like patient experience, patient reported outcomes, very difficult to measure, nationally and locally. And if you can't measure it, people aren't interested in it.., you have to find a way of putting it into a Table or chart, or graph and then people want to see the graph or the other way around once a major change. So, when data is absolutely crucial to this part.'

It is evident here that the service manager again is referring to the cultural aspects that also contribute to the way in which the data is used within the NHS. She further highlights how as an organisation, qualitative perspectives are less valued than measurable metrics, particularly by senior management and executive boards, thus further highlighting hierarchical influences. Central analyst M.B, confesses that: '*there is also the tendency to get a little too obsessed with the data, you can get too bogged down into the detail, but there is a really need to look at the bigger picture and focus on where you could have more impact by changing stuff'.*

In addition to this it was also identified that, everything is driven by the data from performance to financial stats, to infection-control ratings and it is through these that the functional managers have to prioritise their focus. Notwithstanding, the data does not consider everything and as discussed previously, often being in the context and environment offers more meaningful insights than the data could provide, however, the focus remains on what story the data is telling, not the story the functional managers have experienced. This therefore may lead to tasks and projects being incorrectly prioritised, as highlighted by R.G:

'*Most of that is driven by data, it's driven my performance, and stats, financial stats, CQC ratings infection-control ratings, all that kind of stuff. So, it's absolutely driven by data. We have a plethora of reports, dashboards, take*

updates, and which is different way of slicing different data, and that tells me what my priorities are. Not because, I necessarily agree or disagree with them, but because if something goes red, or goes in the wrong direction one of our senior executives says that needs to change, more often or not they are going to ask you how you going to do it? And, so that data has driven that decision but it's not my decision'

Therefore, by prioritising decisions based on the data and not on organisational actors, such as the functional managers is also seen as hindering the impact of BI use, particularly as the data may not provide a complete picture, as R.G further pinpoints:

'See anomalies of things that are spurious and that I am not happy with, I have to ask questions about what is driving that, what's behind it, what do we need to change? And how do I understand the information better, because that's as much as its 'what is the data telling us?, There is also the question of 'what is the data not telling you' in terms of what is not included in that dataset that might be relevant, which might influence the findings.'

It is apparent that the manager knows that the data does not provide the complete picture therefore the data may represent part of the truth but not to its fullest extent. As such, it can be argued that trying to deliver change based on incomplete and partial contexts is why there is a lack of impact and change being initiated. It was established in the previous sections that; the service managers do not necessarily ask the right questions of the analysts or on occasions do not effectively communicate what they are trying to achieve through their requests. Therefore, the role of the analyst in asking further questions is imperative to ensure the correct type of queries are generated, which include all the relevant variables. However, based on the discussions relating to the lack of impact resulting from the BI data, it was apparent that limited discussions took place between central analysts and the service managers during the query building process. It was only when data significantly contradicted the feelings on the ground that, discussions would

be instigated, which often led to contestations. This is also outlined by the central analysts, in this instance, P.S outlines:

'I was asked on something the other day, I had no idea what relevance it would have, but I just basically did what they asked for and sent it out. So, on occasions, there is a bit of a blind spot, but I can assure you it is only going to get worse because we are capturing more and more electronically. I mean in some respects, it's good because you get more breadth of what you're doing, but in some respects it's really hard, as you don't know how useful it actually is'

This provides further insight into what S.S was referring to, from an analysts perspective. The inability to discuss and explore what functional managers require, can lead to BI data being generated vaguely due to 'blind spots' and 'uncertainly' which is then operationalised by the managers, achieving very little impact. Here, P.S shares his concern with the future direction of BI use within the NHS. He attributes much of the challenges to the strategic direction of the NHS, whereby more and more data is being collected electronically, to the extent that there is a data focus, but not impact focus. This was also seen by another analyst, P.S who argues: *'You get into a conversation about it, that's why dialogue is very helpful in ensuring they are getting what they wanted. But that is not always possible, I think if somebody says just give me this, they won't tell you anything more about it, you've got two choices. Either you can say no! Or you can just give it to them.'*

Relating back to the discussions earlier, given the nature and scope of central analysts, they are often working through jobs that are logged through a central system, therefore often it is not possible for them to engage in a discussion with someone who may have initiated a request for a particular type of report, query or analyse. In such instances, the analysts have no choice but to provide the information to the functional managers, without really understanding some of the contextual details or its relevance of how it will impact the wards.

There is an opinion that little change is implemented through the current utilisation of data and ways of working. Though the data is helpful, it is evident that there is a void and dissonance between perceived benefit of data and actual benefit, which is underpinned by many factors, which include skills, culture, and resourcing constraints etc. To summarise these challenges, Group Performance and Improvement Manager, R.J offers some critical insights: *'Targets do kind of, targets are the be all and end all. I understand how much they have on their plate, but it's also a lack of communication and trust, because they never sat with me to learn my world, they see my world from orbit' but are they willing to understand?* He continues*; 'Are they able to go through the detail or is it just to fill piece of A4 paper, to say this are what the trends are. We are very good at telling people what the problems are, but we don't seem to have any detailed steps going forward.*'

Similarly, Performance manager, P.G expresses the inability of the trust to leverage benefit from the data, and goes further to suggest that much of this is down to what people want to hear as opposed to what is the real story:

'We are not understanding all the metrics we've got about our service on a daily basis to then inform how we behave... Instead, we are picking and choosing things that we think tell a good story, and sometimes it's a genuine good story, but other times it's to satisfy what other people want to hear, and I think that is definitely down to culture, and down to the way we work.'

Therefore, the inability to derive value from the data is also seen here to link with how the data is hand-picked to promote 'success stories', thus not necessarily focusing on the entire picture. This was also a dominant theme from the findings when exploring how the data is being used and operationalised, and thus will be further explored in the following section. Moreover, it is argued that this can have significant impact on power dynamics within the trust, as the credence and importance placed on quantifiable metrics is not the natural disposition for many of the functional managers, who have decision making influence, yet are less absorbed or interested in the data. As such, the functional managers are increasingly finding that they must rely on

other organisational actors, predominately analysts, with whom they share an uneasy relationship and disjointed relationship with, as discussed earlier. Table 6.1 provides an overview of the key sub-themes in line with the research participants.

Disparity		
Functional managers	**Central analysts**	**In-house analysts**
▪ Functional managers vs analysts ▪ Conflicting priorities and focuses	▪ Central analysts vs functional managers ▪ 'Us and them' mentality ▪ diveregent interests	• Disputes with managers • More conlfict with the central analysts.
Analyst Incongruence		
Functional managers	**Central analysts**	**In-house analysts**
• Aware of the disagreement between the central and in-house analysts • Generally in better terms with the in-house analysts given their presence within the same enviroments	• The central analysts and in-house analysts were often seen to be in disagreement, • Although in similar roles. This was largely as a result of their corporate and central dispositon.	• Disagreed in the central analysts use of BI. • Considered their use use of BI very narrow and non-contextual
Skills disparity		
Functional managers	**Central analysts**	**In-house analysts**
• Skills disparity between organisational actors. • The fucntional managers were more suited to operational tasks and fire-fighting, • Their insights and inuition was driven by what they saw and experienced during the wards. • Much of their decision-making instincts were informed through their 'gut feel' and 'personal hunches'	• Highly analytical disposition and base their recommendation entirely on what the data was represented • Their strong analytical skill and the managers lack of analytical skills often led to a disjointed and fragmented relationship	• Seen as the most beneficial from the key actors engaging with BI. • They had contextual & insitutional knowledge due to their close proximity to the operational activities • Also had personal, strong analytics skills base. • Effective use of BI, within the context in which it sat. • More favoured by the executive

		board and senior management. • Able to also exhert influence over their managers, as well as the clinical staff. .
Data Vs Intelligence		
Functional managers	**Central analysts**	**In-house analysts**
• Found little benefit in the data generated by BI • In agreemnt of an overview of operations, from a macro perspective • Felt the micro, drilling down functions were not effective as they lacked context. • Therefore, they would refer to the data as a lot of 'nosie' but little 'intelligence'	• The data analysts felt that the BI generated reports led to intelligence • Largely dependent on the way in which it was utilised. • Highlighted their purposes were largely for reporting and that its application within wards was the responsibity of management.	• In agreement with the managers that BI driven insights from the central analysts are 'baseless' and 'misrepresented'. • Felt that by being in the enivironment, they were the drivers of 'Intelligence' resulting from the data.

Table 6.1: Summary of 'Social Pressures' mapped across the research participants

6.3 Actors cognition

One aspect of this research focuses on how BI is being used by different organisational actors within the NHS trusts, as a result various interesting themes emerged from the discussions that were guided through the use of The Enactment theory (Orlikowski 2000). It was evident that managers and the analysts and analysts amongst themselves were using the BI tools in a disparate manner which was influenced predominantly by many factors, including time and target constraints, their skills, motivations and differing objectives. As such, dominant codes generated from the data include intuition; Intuition; Experience Curiosity; Disapprove myths (mainly managers); Data vs Intelligence and Data Manipulation. Each one of these will be explored in detail to see how it influences the eventual application of the BI tools and its implications for power dynamics within the organisation.

6.3.1 Intuition – '*The gut-feeling is almost always right'*

The narratives revealed that the BI tools were used in different ways by different actors with obvious reference to the previous section, this divergence was underpinned by the roles of the organisational actors, their skills disparity and the personality traits held by particular groups. Nonetheless, it was evident that output from BI was being used intuitively by the functional management. Interestingly, this intuition was informed through their experiences, gut feelings and also the data emanating from the BI systems.

From the context of the service managers, it was evident that despite their limited analytical skills, they was still obliged and expected to liaise with the analysts in order to operationalise the data produced in the form of reports, dashboards and graphs. However, it was clear from the discussions that the service managers were using the data as means to validate their gut-feeling and personal intuition. This is evident when service manager, A.H highlights: *'so, trying to nuance some of the black and white of the numbers I suppose against, experience and knowledge of, you know because, the clinicians and*

the admin and nursing team have really, in depth gut feeling, that I suppose that they can bring into that as well.'

It is evident that the service manager, whom in this case is also capable of analysing the data due to her previous background, also heavily relies on the gut feeling and experience of her team, which included the clinicians and admin staff. It is therefore through their intuitiveness that she has the ability to make sense of the data, as she feels the objectivity of the data can be offset by the subjectivity from within the wards when making decisions. This approach was favoured by several service managers including, deputy service manager, R.G, who would also confer with others as a means to fact-check and validate his assumptions: '*Sometimes you want to speak to somebody who does the same job as you in a different area, to see if they see the same way I see it, but by going on speaking to the clinical director or the surgeon, you are getting a different perspective on the same information. Again, you are validating your gut feeling versus empirical fact.'* R.G, similar to A.H, prefers having a discussion with someone who understands operational dynamics and has practical experience, be it a colleague from another part of the organisation. Therefore, if his gut feelings are challenged by the data, this process of articulation with his colleagues allows him to validate whether to trust his instincts, or to go with the data.

R.G, provides details of how he manages his personal assumptions and gut feeling with empirical data: '*The way I start using data is, we have assumptions, feelings, intuition, the first thing is, how does the data interact with my gut feeling? So, if I am looking to evaluate a service, and I look at the data and the data gives me information, I would evaluate whether that feeling is a million miles away from my gut feeling? Or does that confirm what I thought I already know? Does it challenge my perceptions? So that's the first thing, the second thing is what does the data give us? It rarely answers questions, it's more often poses questions.'*

Furthermore, service manager J.A also highlights how he uses the BI data, but more importantly how this BI data is applied to his personal experience, in

order to get ‘a feel of the data’. He posits: ‘it’s partially intuitive based on experience, but it would be a trigger just to check the veracity of the data.. I like the option of having the data at my disposal’. This highlights that in order for decisions to be made off the back of the data, personal experience is often used as a means to validate and check the appropriateness of the data provided. However, it may be difficult for functional staff who may not have the practical experience to validate the data for decision-making, as will be discussed little further. He goes on to state: ‘I think it all informs it. If that’s a good way of putting it? Because, you’re looking at the data and have some understanding of how the data is, so the intuition is really based on looking at the data and, and understanding where the data has, has a feel that it is correct.’ Again, J.A refers to role of experience, and how looking at the data builds up his personal intuition. Therefore, in the case of J.A, data plays a major role in how he is able to build up his experience and intuition from his functional disposition. Another contributory factor that may explain this methodology is the fact that J.A also has a clinical background, therefore has experience of understanding and using data. However, this differed for other functional managers, for instance, L.B, deputy operational director was not as reliant on the data in the first instance. This differs from J.A, who suggested that he uses the data and then validates the data against his intuition, which is based on his experience of reviewing and interpreting historic data.

Whereas L.B, uses the data in order to approve or disapprove what she is already convinced about, as highlighted in the following statement: ‘So I often use it as the secondary thing, rather than the primary thing. If that makes sense? I know what I am looking for and then I will simply check the data to see whether that is correct or not you and that is informed through the knowledge and experience I’ve built up through our conversations’. L.B highlights that she relies on her experience and personal intuition which is grounded in first-hand experience of what happens within the wards, which is underpinned by many conversations, discussions and observations. Therefore, the data is only really used as a way of seeing whether she has the correct impression of what is actually happening. She adds further: ‘I think my

style, I think if you get a blend of different personality types and ways of working, you get the best of both worlds. I'm a big advocate of, it's not just about data, it's about group dynamics, it's everything, everything. Everything has to come together and it's all, it's almost like a Venn diagram, you've got people's got feel, and then the information then layers over that, to prove or disprove the gut feeling, and it is only then that I think the analysts and their data comes into it'.

Interestingly, she states that that even before she is exposed to the data, she has already validated her gut feeling and personal hunches through the discussions and the layers of information resulting from these discussions. Nonetheless, she does value what the data brings as it helps her balance her intuitiveness and subjectivity, this was further outlined in the following by L.B: 'so I think, it helps me be objective, because I would be off the scale intuitive otherwise. So I have to work hard to remind myself, it's not just about how I feel, that there's more to it than a gut feel. You need an evidence base for most decisions yeah and I need it, and I need my analyst around me to remind me, that there's more to it than gut feel (laughs)' L.B emphasises the fact that 'she needs the data' as this provide her with an evidence-base and also helps balance her intuitiveness. This ties in with early discussions which emphasised the data driven nature of the NHS and how the managers are expected to evidence their decisions based on the data, rather than solely their instincts.

Additionally, General manager, G.T also highlights how she attempts to mediate between her personal intuition and experiences and the objectivity provided by the data when she states: 'Then I'll go, tell me why I am wrong, then I will go, prove to me I am wrong. So then, the information, and so, yes, it is very much on my intuition, but I work hard to prove, I mean I know I keep repeating myself, but how dangerous just working of gut feel could be, and I know that's my, I know that's my natural place. The self-awareness forces me to do that.' It is evident that she relies firmly on her intuition and experience however if the data opposes her gut feeling and intuition, she will engage in a detailed discussion with one of her analysts and will only be satisfied once they are able to answer why and how her intuition was incorrect, in doing so she

also acknowledges how just relying on the gut feeling is dangerous, particularly when the data and analysts may disapprove her initial assumptions. L.B also highlights how she questions herself, which also plays a part in the build-up of her intuition*: 'I like things to hook back onto, to go, 'oh, why is it that I'm feeling like that?!'.* Therefore, she acts reflectively and questions why her gut feelings may be strong on certain things, and this cycle, which involves gut feelings being informed by her previous experiences, conversations with colleagues and her reflective practice of questioning why she believes her gut feelings are strong, is an ongoing process which informs her overall intuition.

It is evident from the perspective of operational managers, that they rely heavily on their personal intuition which is amassed through operational experience and sense-making. However, in exploring how BI is used by the analysts, it is also evident that they won't rely on their intuition and instincts when providing support to the operational managers. M.B highlights: *'My intuition is principally the building blocks of knowledge, as I go along. I am fortunate to have worked in a few roles within the NHS, so lot of similar problems come up, for example when people are asking certain questions relating to the data which I have dealt with before, so you know how to, you know how to pre-emptively stop that issue from occurring or happening.'* Through working with the data, M.B is able to ascertain the types of questions managers may ask, particularly if it relates to re-occurring problems that require addressing. Importantly here, he highlights how his intuition is also based on previous roles within the NHS, thus allowing him to understand the context behind questions, conversely, he states: 'y*ou can only intuitively look for the clues in the data if you're aware of the contextual details, I often struggle with that, particularly if I am running queries for people who I've not worked with before'.* This again indicates the importance of knowing the local context and therefore suggests that in order for analysts to be intuitive they would require background knowledge and solely looking at the data would not suffice. These views were further emphasised by the clinical information manager, J.D who states: 'If people know their own service, their gut-feeling is almost always

right, 9/10. Therefore, when the data contradicts this, we don't really let it challenge our perception'. This further highlights the significance of knowing the intricacies of one's service, and the role it can play in also countering the data.

The Performance and Improvement manager, P.G, who also has analytical skills and responsibilities also acknowledges personal intuition as being 'something you know and are aware of' which allow you to 'typically know what to expect due to being in the environment' therefore, argues that through also having a local disposition within the directorates, allows the in-house analysts to be more intuitive:

'There is an element of having seen it before, you typically know what to expect, so you could identify a special code in your head, a good example is we had, a pre-visit call week, which was a week last year where all of our Outpatient appointments were backed up with a call to our patients on the day before, as a reminder to our patients regarding their appointment the following day, this meant that some patients that would have DNA'd, made sure they attended, what you will therefore see is a reduction in the DNA, that one week which you would know unless you, sat down on the floor knowing that that week had occurred. Therefore, there are many examples like that which you're making an extra effort on, which you know about, internally.'

Not accounting for the events which occur within the directorates therefore can result in limited insights and essentially lack of intuitiveness. This is further supported by P.S, who posits: *'When I began running queries more regularly for the labs, using lab data, that wasn't straightforward. Because it was different data sets, so I had to learn what the trends are, what we would expect, how many tests we would be expecting, in different areas. So I guess, there is an intuitiveness with the data in general, such as seasonal trends and there is also in intuitiveness with the dataset specifically in the area of whatever work you are doing in the NHS or where ever else you are working.,. Does that make sense?'.*

Here, P.S states that there are general aspects that the analysts are able to identify, which may be based on seasonal variations however, analysts who are not well acquainted with the finer details of how a ward operates, may find difficulty in building on their personal intuition. Interestingly, the in-house analyst R.L, supports this despite his analytical disposition, he argues*: 'it's a lot, if the data is saying something I do try to get, I often try to get a doctor or someone to say does this fit with your with your belief, if not, then I might have done something wrong. If you know what I mean? If the data is saying one thing and the intuition of the ground is something completely different, I would often say the data is wrong for some reason…'.*

In circumstances whereby, the intuition of the operational staff differs from the data, it is expected that R.L, being an analyst responsible for producing the data, would disprove the intuition and rely on his data. However due to him being in the context, and having localised knowledge, he would question his data and not that intuition and gut feeling of the operational staff. Thus, this highlights the role and importance of having background, domain knowledge of what is happening within the wards for intuition build-up. This differs considerably to how the central analysts would contest intuition of the operational staff and instead favour the data if there was a disagreement between both, as highlighted by central analyst, S.K: '*I mean the data is subjectively saying that that's not happening so sometimes people aren't always happy with what the data shows but I think that's why it's important to be able to use the data and have that objectivity and supplement people's hunches because I think that's, yeah, the data. Yeah. Data doesn't usually lie does it? But peoples hunches can be influenced, perhaps by biases and preconceptions (Laughs)'.*

Supporting this, M.B also operating centrally as Business Intelligence Officer highlighted*: 'we do listen to what they have to say but at the same time like, but there's only so much you can see as an individual within the ward whereas the data could look at everything.'* This highlights the disparity between how the local in-house analysts and the central analysts manage their operational colleagues following disagreements over what the data is representing. It is

seen that the in-house analyst takes more caution and looks at exploring the intuition on the ground whereas the central analysts are seen as a generally disapproving the intuition and backing their data.

Informatics Enterprise Architect, S.S weighs in on this incongruent approach, when discussing how data is being used within the NHS and highlights: *'the problem with this organisation or lot of healthcare organisations, they lack the framework and structure therefore they have to make judgements based on their intuition and depending on the knowledge and expertise on the individual based on the learning, you get the output..'* He is critical of the fragmentation and lack of consensus within the NHS and therefore believes that colleagues often rely on intuitive decision-making as opposed to relying on the elements to support their decisions.

In summarising this, it is evident that the organisational actors rely on their intuition and this varies between the functional managers, whose intuition is guided and informed through what happens in wards, whereas conversely, the analysts refer to the intuition based on their knowledge of data-sets and general knowledge of reoccurring trends during certain times of the year. Importantly, it was evident that functional managers prefer to articulate between themselves when the data conflicts with their intuition and gut feeling, as opposed to referring back to the central analysts, particularly as these analysts would be disinclined at acknowledging the intuition on the ground and would be more in favour of the data they provide. Alternatively, it was seen that the in-house in- analysts were more open to deliberating and exploring the gut feelings and hunches of operational managers, particularly if it opposed the story the data was propagating. This was due to them also being embedded in the environment and also sharing part of that intuition and gut-feeling, due to their proximity to the wards. Therefore, it is argued that articulation occurs more between organisational actors who are exposed to and share operational intuition.

6.3.2 Curiosity – *'my curiosity allows me to cut and slice the data in different ways'*

The findings thus far have revealed that the functional managers and analysts use BI in divergent ways. The managers extensively use the BI tools as a means to fact check their own personal tuition, the central analysts produce generic queries based on their jobs list and take a data driven approach, and where required also challenging the intuition of operational managers. Conversely, in-house analysts were more open to 'gut-feeling' and 'operational instincts' and benefited from their local knowledge, which allows them to produce more tailored BI output in the form of queries and reports. However, another interesting theme that emerged from the data particularly when speaking to the analysts was the role of curiosity, and the curious nature of the analysts. Although both central and in-house analysts were seen to exercise some curiosity in their role, it was in-house analysts and only the central analysts who have had previous experience of working in an operational environment, who are able to guide their curiosity more effectively.

For instance, J.J states: '*Just through things, me messing around with different reports that already exist or data that I could turn into nice graphs and things that actually demonstrate something useful to the, to the executive group. And I don't think that would have happened if I was just not curious about what I could do with it. But that does come back again to, working in that operational, managing the admin kind of role a lot of that involves the clinicians coming to me when they weren't happy with something, or there was a lot of stuff to do with waiting lists and how they would be managed. So, I think a lot of me working in that role has given me the ideas as to what could go into this performance report that would be useful'.* Through J.J's personal experiences of working in the ward and her exposure of the dynamics from within the operational context, makes her more curious by nature in her role, therefore she believes she is able to produce better results for the functional managers as she is able to take into consideration for the factors which may not be picked up by analysts without this operational curiosity.

Notwithstanding, this does not imply that the central analysts lack curiosity, they were also found to be curious, yet given the nature of their role, the application and pursue of their curiosity differs to that of the in-house analysts. For instance, this was reflected by central analyst, P.S, who states: *'yes curiosity is a really big thing it is a big part you, think, you keep uncovering things forever, so you have to, I find that difficult to control you have to really sometimes because, you could just end up spending ages and end up not getting anything done (laughs)… You'll send some information, and you think 'uh!!..let's look at that, and you can end up doing the same query with a bit added on!... for ages!, because you'll get down this lane and think, no!!' Just stop.'.*

As discussed further in section 6.4.4, it was revealed that the central analysts were operating in intensive, target-driven environments, therefore most often were bound by time constraints, due to the volume of tasks and request from across the trust. Therefore, they were restricted in the amount of time they were able to allocate in pursuit of their curiosity. This was seen further, when another central analyst, S.G acknowledges his curious nature but states: *'Obviously my own curiosity, does come in every now and again and am interested in why somebody has asked for a particular set of data, but unfortunately I really don't have the time to delve into it too much.'*

Supporting this further, the service managers were also in agreement of this. The lack of creativity and imagination of central analysts resulting from time constraints was also picked up by one of the service managers , A.H who highlighted; *'I think we are still at a point where not enough information that is regularly wanted is self-serve, they are often building things on request and they probably don't, I think, I'm sure you've picked different things from different people but, I wouldn't be surprised if that was frustration of theirs, maybe they don't have the freedom to go and hunt for the own things'* This resonates with what the central analysts have highlighted in that, they struggle with time given the target driven emphasis of their role, therefore are unable to offer creative support to the managers. On the other hand, L.B, who also

has access to his own business analyst provides an alternate view, when he posits: *'We have a really strong relationship with ours and they've been here for a while now, she's came to me and said, 'oh yes, I've spotted this,' which to be fair, they do, they will be like 'this just doesn't look right, or everybody has been talking about this, why do we do that?' But, because they are a shared resource, you have to buy into that. If you were a directorate with your own business analyst, it might be a bit more free, but it's about resource isn't it? And capacity..'.* This further supports the fact that the in-house analysts, who are also a contested resource are able to operate more freely and creatively than their central analyst counterparts. Much of the curiosity which informs the in-house analysts results from exploring the data, but also being aware of the local context, whereas the central analysts only have the data to go at therefore, with them lacking some of the background knowledge, makes the curiosity less complete and more ambiguous.

It was also apparent that the managers also exercise curiosity when they look to operationalise the data and it is through this curiosity that they are able to triangulate between their personal intuition and experience and what the data is representing. This was evident when L.B state*: 'So how it works with my teammates, I generally have a thought about something, and I'm quite curious. I come at everything with curiosity… I need to tell everybody we need to improve, actually if you take a minute and step back from it have a curious conversation with an expert, you're then being able to horn in more quickly on the "so what" of it.'* By taking a curious disposition, the manager can probe the analysts and her other operational staff, which allows her to collectively reach answers more efficiently. The importance of being curious as service manager was also highlighted by A.H, who stated: '*so my curiosity allows me to, cut and slice the data in various different ways. It's pretty much in that order. The first bit of knowledge, in the data will take me down different routes.'* Therefore, when exploring and attempting to interpret the data, the service manager usually favours an inquisitive approach, which allows her to see perspectives on the data.

The ability to make decisions based on the data requires the aptitude of generating relevant questions from the data, this was seen by R.G, when he outlines the role of his personal curiosity in making sense of data: *'It rarely answers questions, it's more often poses questions.. I use data to ask questions, I use data to ask questions that leads me to ask other questions, I need more data I need more detail, I need different types of data. So I tend to go around in a circle and drill down into the detail, those decisions will shape, the type of decisions I will be making off the back of that.'*

Therefore, relating back to the theme of BI application, it is evident that this curiosity does play a role in how the BI generated data are used by both the functional managers and the data analysts. As identified thus far, there again is a clear difference in how the in-house analysts and the central analysts operate, and it again seems the local, contextual insights of the in-house analysts enables them to better exercise their curiosity when compared with the central data analysts, whom due to their target driven, fast-paced roles are less successful in exploring their curiosity.

6.3.3 Disproving myths – *'at least the data helps bust myths'*

Another interesting finding when exploring how BI is used within the NHS trust was that of, 'Myth busting' or 'Disproving myths'. While it was acknowledged in the previous sections that the data can challenge managerial perceptions and assumptions, the BI data was proven to be valuable to functional managers when they were required to disprove and eliminate common myths regarding particular services within their remit. Therefore, it is argued that, other than for decision-making purposes, the BI data is also used extensively in this regard. This was highlighted when service manager, A.H outlines: *'so there were a lot of assumptions about what that would tell us, you know people would be like 'patients don't want to come, because of X, Y, and Z' or people would say, ' DNA (Did Not Attend) rates are really dreadful in the evening, or a Saturday' and then, and this piece of work was done and lots of, lots of those myths were immediately quashed and that was, we had a task and finish group around this particular issue'.* Although this particular work would indirectly

assist in managerial decision making, the emphasis here is placed on how it was able to eradicate myths that people popularised within the trust, as such proving to be highly valuable for the service manager.

The data was used not only to disprove the myths of others, but also to validate personal opinion and to some extent act as a comparator for one's own assumptions. Specifically, business manager, S.C, highlights the role of data in validating personal beliefs: *'data increases a person's knowledge for sure, data gives substance to what you either think, it proves or disproves what you believe to be happening in your area'.* This represents a form of trust that the functional managers may have in the data. This is further highlighted by L.B:

'So I, so I use it to triangulate the position, so that's one thing, and use it to approve or disapprove what I believe to be right from feeling sensor, I will use a different element of the information to prove or disprove, what data, does the evidence back up what, what people are telling'

This theme was evident throughout the narratives, whereby the functional managers would highlight the role of data in disproving myths as highlighted by the following functional managers:

'yes, yes, myth busting, yes there is definitely an element of that. And having access to decent data, to challenge performance, but also driving improvement is important.' – P.G

'Personally, how I personally you say is, and come up with an opinion, on something and then I used the business intelligence around me to prove or disprove what I intuitively believe to be true.' – L.B

While the previous discussions have indicated that managers may not necessarily be comfortable and open to the idea of basing their decisions solely on the data, it was clear that when it came to myth busting and overcoming incorrect notions, managers were very open and supportive of the use of BI generated data. However, some managers also took it a step further and instead of using the data to disprove myths and personal assumptions,

they would also use the data, in order to prove that the data was incorrect. This can be seen to be the case for L.B, who stated: '*I am not that interested in the details of the monthly performance report, I'm more interested in finding out, where is the data wrong?, so, practical example. We have got, you know in our community services we have a whole bunch of open referrals, with the deceased rate.. But that can't be the right clinic? Because if our client group has deceased, then we have an open referral, so am coming at it, and a lot of what I do day-to-day is, where is the data fundamentally wrong?'*

Due to her operational focus, L.B actively looks at how she can prove to her-self and her colleagues that the data is not always correct, as such her motives of sieving through reports and performance metrics are to prove it to be wrong, against what is perceived to be correct. She does this through her extensive knowledge of how the operations run and therefore is able to apply her contextual knowledge. However, some of the functional managers were seen to use other analysts for similar purposes. This was highlighted by, the clinical analyst, S.P: *'If we can prove what the manager is feeling through the data, that's great, but if we tell them something opposing, that is a different story, then they will see if they can get another analyst to disprove what we have provided..'*

Similar attitudes also held by J.D, who would engage with the data, as a means to establish its validity: *'the data is great, if you've not been working here for a while and don't know the wards out of the back of your hands, when you do, you take the detail with pinch of salt especially if it may be suggesting something against known facts'.*

While the data was extensively used to disprove common myths and notions, it can be seen here that the general knowledge, and commonly agreed upon facts were also being used to disprove the data. As such, it can be argued that the when the data favours the managers, they will extensively promote it, however when the data is in contradiction with their personal feelings or against what they believed to be 'known facts', then the managers would exercise more caution in its use. More specifically, when managers recognises

a direct benefit of using BI data, they are more likely to promote and use it. Therefore, this explains why BI data was used more widely by managers to disprove myths than for decision-making purposes, as highlighted earlier. This is evident from L.B, who highlights why she exercises caution when relying on data for decision-making:

'Different things would have influenced the outcomes and information, you need to use it carefully, because it will not predict you the future. Which is why maybe I am nervous of it, why I use the information to disprove stuff, not predict stuff. I use it to disprove something, because in my opinion it's a good reference point of what the future might look like, if everything else is the same. You probably get the same outcome. So it's, it's a reference point, and you could prove and disprove it'.

It is evident that, because much of the data is inherently descriptive and focuses on historic data, it can be seen as a measure to inform management how well their services are performing, however as discussed by L.B, management tend to be more careful when using it to predict future trends and thus, rely on supplementing some of the historic, descriptive data with the feelings and views held by the ward services staff. Nonetheless, the underlying purpose of data is to provide some objectivity and introduce factual insight into the operations, it is also apparent that the service managers would extensively rely on the data in order to overcome false belief and incorrect notions regarding their services. Therefore, using BI in order to disprove myths and false notions was identified as a common practice for functional managers.

6.3.4 Personalities – '*it's all about the tribe, our tribes share particular traits'*

While it was acknowledged that contestations were due to divergent skill sets and roles, another contributing factor identified in the analysis was the personalities of the organisational actors. This phenomenon again was more prominent between the personalities of service managers and other functional

managers and that of the personalities and personal attributes of data analysts.

The personalities and attributes shared across various groups of people was evident from within the findings, which also contributed to the contestations. These, in conjunction with the skills disparity resulted in an interesting and often tense situation. Service Manager, A.H posits: '*I think you do tend to find with business analysts that, that they want an answer, and ideally want that answer to be quite neat. You'll find that with doctors too, but I think that's more about the background right from, youth and education'.* Here, the service manager categorises what she believes to be shared traits between the business analysts and also some of the clinical staff in that they often want an answer to be quite neat, objective rather than ambiguous and abstruse. This, can be contributed, not only to their responsibilities and the nature of their roles, but some of their background and educational history.

Furthermore, L.B sheds some light on how she perceives herself in an operational role, when compared to her analysts: *'Personally I am not a details person, if I have to sit and do any detail, personal attention span is quite short, and my boredom levels are quite low. So I'm always looking for the party, where can I have one?,* she continues by further stating: *'whereas my analysts, they really are the opposite! They love the detail, they have amazing attention spans and to be fair they don't get bored with it'* It is evident that L.B is categorising herself as being opposite to that of her analysts, while she is less concerned about the details she believes, her analysts are all about the detail, she further attributes to personality: *'I would label it in two ways, I think we say it's a time pressure and personality types, of the traditional analysts. Because they are very introvert in nature, so they would sit in their little world, and you know, I'm very much opposite. Therefore, I push them to be out there, I go and sit with the P.S (Senior Analyst), but their uncomfortable. So I think it's more about the personalities than the time.. As if it was a priority, you would make the time. We've all got time to spend our time, however we choose to do it'.*

Clearly, she believes that the analysts, particularly the ones she has encountered, share similar traits and are introvert by nature, which when offset against her own personality can lead to an uncomfortable situation for all involved. However, L.B believes that by identifying this allows her to retain communicate accordingly, which she believes can help bridge the gap, both the gap created by the skills disparity and personality disparity. She explains how she does that:

'yes, absolutely and I think, by doing that personality profiling it's helped me pay attention to how little, so in the one-to-one way done, attention to detail and the nerdy stuff is the Blue colour, yellow is very outgoing and very vivacious, and whereas the party at?! 'And my blue is tiny. And they describe it as an conscious and unconscious, my unconscious is really low, so I dialled it up, in my work world I have to dial up my analytical bit of it because it's so subconsciously not there, so I have to consciously work hard. You know the learning cycle, unconscious, incompetence and all of that.. I'm kind of, I recognise in myself that I am consciously incompetent, and that I have to keep working at that, so I could use it, so I like to be surrounded by my opposite type, to remind me about that.' L.B users personality profiling as a means to manage her analyst and actively communicates personality profiling to the rest of her team in order to help them identify who they are and how they can enhance their interactions with their colleagues, who may not necessarily share similar personalities.

Interestingly, another functional manager, P.G also has experience of personality profiling, also known as 'Insights', however has an opposing view to L.B: *'yes, so we have insights for me, we was insights as we have 30 people in our team and we've done that profiling, and it sort of indicates personality types, preferences for basing decisions in information fact this is intuition I suppose. But, for me personally, I tend to pay less emphasis on that, because sometimes, it could act as an excuse to go about things in a way that, might suit you. So, you know I am a yellow, so I'm just going to go for it, or whatever, so yeah.'*

While he acknowledges the usefulness of such tools, he feels that it can be used by colleagues to justify behaviours and traits, which can be counter-productive and detrimental. Nonetheless, in support of the sentiment outlined by L.B, it is clear that some of the analysts demonstrated very similar characteristics. This is evident from the central analyst P.S, who outlines '*I'm comfortable with taking stuff home and doing work at home, because I find it interesting. I know I'm sad aren't I? (Laughs). I love getting into the nitty gritty and learning new ways to get things done, so I won't stop till I get to the bottom of something.'*

This is in line with the traits described earlier, whereby the analysts are described as having higher attention spans and do not get 'bored' or 'disengaged' by exploring the data, whereas some of the functional managers would. This is further seen when, J.J mentions: *'I'm always messing about (with the data), now you can see why I don't watch much telly can't you?',* this further highlights the introvertly curious nature of the analysts. Another interesting viewpoint to personality traits was raised by service manager A.H, who highlighted: '*it's all about the tribe, our tribes share particular traits, analysts, as a people also share similar traits to each other, I mean, we are about the conversation, getting to understand through conversing whereas for example the analysts may not necessarily be able to explain things in a conversation, yet produce fantastic work independently'.*

Here, A.H emphasises the fact that organisational actors associated within certain groups tend to share similar characteristics and traits. She goes further by highlighting that while the analysts are technically and analytically superior, they may struggle to articulate and convey their understanding to other organisational actors, which can potentially lead to a lack of agreement and consensus.

This interestingly, was evident during some of the conversations with the analysts, R.L, who was unable to clearly explain the implication of target pathways: '*It's five questions what it stands for, it's basically replacing for the non-re-agreeable pathways, what we would instead… sorry other people may*

be able to explain far better than me,', a similar instance was further seen by analyst P.T: *'I can try and explain, but we'll still be here next week! (laughs)'* and further supported by R.L: *'so this is my line manager, she is the deputy operational director for the whole care group. Yes, I did try to explain to a face-to-face, and still couldn't. Properly anyway!.* Therefore it seems the analysts themselves acknowledge their inability and to explain as adeptly as some of the extrovert functional managers may.

S.C further mentions*: 'it's the personality and confidence to challenge and ask questions, but keep the sense of objectivity about what you are undertaking. In fact the numbers have dropped a tiny bit this year and that's where I think, my experience and my personality, I have to go back and challenge, and say actually! Your overall workload to your commissioners needs revisiting, I think I'm tenacious and have to be in this role!'.*

It can be argued that although the analysts continually referred to their interests and underlying motivation of getting to the bottom of particular tasks and, the functional staff conversely emphasis their desire to initiate conversations and discuss matters in person, due to the gap in skillsets and understanding.

General manager, T.H emphasises the disparity in personalities and his experiences of interacting with introvert analysts and their reluctance to engage:

'So have you been to the central performance office, in the corner? So I walking, and I'm probably my normal self, but for them, they'd think I'm right over the top, I'm sure! So I'm like 'hi everybody!!', And you can almost feel, you can almost cut the air, when they're like 'oh god, someone spoke to me!, oh my God, somebody spoke to me!', and I'm a bit deliberate on it, so "I'm like oh hi how are you?" Only a couple of them are more likely to engage, others don't, and I think, I think they are naturally introverted in my experiences. And that's okay, you need that, however the risk is, when it's a bit like nursing, you have a lot of the same type of people within nursing, and they couldn't care

less about the data, and generalising, but mostly they are like yes whatever, and so, actually what you need is a real blend.

Here, another functional manager provides further insights into the fact that the analysts are not eager to converse. However, in this instance, T.H is not referring to discussions relating to data produced by analysts, but rather mentions this in context of a general discourse and dialogue, thus further emphasising the reclusive nature of analysts as highlighted by the functional managers.

This is further evidenced when R.L discusses himself with other central analysts: '*To be fair I would like to think so yes I'm not, I'm certainly not more clever, in terms of data then the information services team. I'm not, I think it may be down to different motivation. I want to be right, and I'm quite pedantic, you know, I think it helps me my role been pedantic and yeah.'* According to R.L, while he doesn't consider himself technically more superior or 'clever', then the central analysts, he does consider having different motivations which allows him to deal and work with the data in other ways than the central analysts. He focuses on his pedantic nature as a means to explain why he would persistently explore something till he is able to Figure it out. Again, this ties in with the *'getting stuck in the detail'* characteristic used to describe the analysts.

As such, it can be argued that due to the time constraints and the busy nature of their work, there is little interaction or personal meetings taking place between the analysts and the managers. Nonetheless, the opposing personality traits and characteristics shared by organisational actors is also found to contribute to some of the tension that is built up during these interactions. Therefore, in summarising the contestations, it is evident that a plethora of factors were identified as contributing to the disagreement and disengagement between various stakeholders resulting from their use of BI. Much of this was due to divergent roles and responsibilities, unmatched skills, personalities and mindsets. But importantly, and in the context of this research it was evident that the contestation was firstly resulting from the use of BI, but

also contributed to, by the personalities of the users, which had particular implications in relation to power dynamics within the organisation.

6.3.5 Data Manipulation- *'I'm not an analyst, I'm a manipulator of figures'*

It is therefore becoming apparent that based on the discussions and findings of thus far, that the data is being used in a way that is not initiating change or having an impact on operations in the way it is expected to. Much of this is attributed to the overarching focus on the data and the 'obsession' of publishing and disseminating reports and graphs that highlight trends. It was also clear from the findings that the service managers would use the data in a way that best represented their interests, which was only possible through having a good relationship with the analysts. As previously highlighted, the central analysts and the functional managers do not share harmonious relationships, therefore this act of 'data manipulation' was more successful and commonly associated with managers that had access to local, in-house analysts.

While the findings suggest that managers do not base their decisions entirely on the data, with them often trying to disprove the data through their personal, localised knowledge, the managers were found to rely heavily on the data for various exercises, such as for a business cases. As such, displayed an important role in the power dynamics within the wards and particularly between the analysts and the functional managers. This was seen for instance, when L.B discusses the importance of data when persuading the senior managers and the board:

'It's a give and take, and sometimes when they do business cases, they will, they will game it. So I think, if that relationship is tight, they could game it. So if there writing a business case for the board,, it's like what are you trying to prove? Right, let me go away and prove it. And then I like to think, that I come in and be the, kind of devil's advocate. You *know, and I am the independent*

broker in the middle of it all, so yeah, so I think the analysts, you have the information which enables you to game, operationally'.

L.B places emphasis on the 'tight', close-knot relationship between the manager and the in-house analyst, who have a harmonious association between themselves. It has already been established from the findings that this relationship is not always conflict-free, nonetheless it can be argued that in such circumstances, the in-house analysts can capitalise on their expertise, in terms of their analysis skills, their ability to manipulate the data and their local context knowledge, to exert influence and impact the power dynamics, particularly given that functional managers are highly reliant on them and their skills, particularly if 'gaming' or some form of 'creative representation of the data' is required. This can represent a shift in power dynamics particularly as the analysts are inherently lower in the organisational hierarchy compared to the functional managers.

The importance of a business case and a white paper within the NHS was also highlighted by performance manager P.G. He outlined how the strategic, long-term vision of the trust is underpinned by business cases which are expected to consist of impressive -looking data and persuasive white papers. He states:

'As bad as it sounds, it seems to be the way things are done. One person calls the shots, there'll be a White Paper attached to it, and there we go, everyone will be like, yes let's go with it. The numbers look good. That is something that I have picked up..'

Therefore, in order to initiate change and influence decisions, the ability of presenting data and supporting your arguments through the representation of analysis seems to be an essential and re-occurring theme from the findings. While managers may be reluctant to rely extensively on their analysts for daily decisions, as established previously, managers must rely on their analysts when pitching and persuading the senior board for their proposals to be considered. When referring to data manipulation, it was evident that the managers were reluctant in disclosing too much information and would continually justify it by stating that it was more about having another

perspective on the data, as opposed to data manipulation in its actual sense. This was seen by the following functional managers, who outlined*:*

'of course, it has to be within reason. You cannot just make up a story from the data, the idea is about trying to be more creative in your representation of the data'. – Service Manager, A.H

'yes definitely manipulate data, not manipulate, that's not the right word. You can, choose to focus on one aspect of the data' - Business Manager, S.C.

Supporting this further, service manager N.A outlines the importance of tailoring the data and presenting it to a diverse set of stakeholders:

'so for example, if the numbers weren't great, I would focus on a different part of the data, so what I would do is one of the big things around this assessed work is saving admissions, so we show impact by the bed days we have saved. So if we avoid one patient if we did admit that patient his length of stay would be two days. So if we saw 10, that would be 20 bed disabled but when I write a paper, the attendances other same, but when I write paper, I will focus on other parts of the data and perhaps write a bigger paragraph on the fact that we are saving so many bed days. So it's how you tell the story that goes with it, but with my own team, I would say we need to do more and see more patients, however outwardly, I would present it in a different light'

As such, having the ability to focus and to interpret particular parts of data according to diverging stakeholders, requires analytical skills, or the ability to negotiate with the analyst, so that the correct story is being conveyed to the appropriate audience. While this may not be considered manipulating the data, it can be argued that it certainly is sensationalising the data in order to achieve the best outcome. This again requires the skills of an analyst, particularly the in-house analyst who can understand both the technical data and the contextual insights. Service manager, J.B, emphasises the reliance on the analyst when stating: *' you can make the data tell you what the hell you like! But the analysts is extremely important for us, they hold the key, as for the*

gaming, I would, I hold my team, my analyst account to not game too much. You know what I mean?. '

Conversely, from the context of the analyst and supporting the fact that the in-house analyst has influence in such circumstances, analyst J.J outlines:

'it happens quite a lot I guess? Particularly whereby when the service managers will see the data that you are provided in a report and then come back and ask you whether it could reflect a little bit more of something else or it could be focused bit more specific to looking at something other than what the report is saying. To be honest I think, the current people who work with now have probably heard it enough from me that, if I say it can't be done it, can't be done! I feel like it used to happen a lot more than it does now, or maybe people have just stopped asking! (laughs!) Have been persistent in saying no!'

Here, J.J is clear that she refuses to do so and that her operational managers have stopped asking her due to her persistently refusing to 'do more' with the data upon the request of her managers. This therefore highlights that the functional managers do require the analysts when they are wanting to focus more on particular aspects of the data. This was also seen by in-house analyst, R.L who highlighted that functional managers would not only request data to be manipulated for only business cases, but also to reflect good performance in the services, particularly around what may be the wider area of focus for the trust as a whole. This can be seen here: *'If something is hot, and it is the flavour of the month, you could sort of come up with any anything if you really wanted, if you really are looking for a story, we can manipulate it to make our service look more impressive than it is, we have that amount of data.. But what I tend to do is I ask is there actually a story there?'.* Expressing caution, R.L states that while he has the ability to do so, he will consider how plausible the story may be, prior to considering it.

This points to the fact that analysts require the analytical skills, the contextual knowledge and also the creativity in order to tailor data according to various organisational actors. While the central analysts have the skills, they lack the

contextual knowledge and the time to exercise such creativity and personalisation. Thus, further highlighting the difference in the service offering between the central analysts and the in-house analyst. What can also be gleaned from this particular code of data manipulation is that, the power dynamics are seen to vary given the circumstances and the situation, with dynamics of power shifting in the favour of analysts when the management require them to exercise their expertise and skills in particular situations. Table 6.2 provides an overview of the key findings for actors cognition across the key participants.

Intuition		
Functional managers	**Central analysts**	**In-house analysts**
▪ Highly reliant on intuiton and often preference over BI data	▪ Acknowledge intution, ▪ Pattern identification in data, ▪ Limited reliance on intuiton.	▪ Intuition via first hand experiences within the wards. ▪ Supplement BI data with 'intuition on the ground'
Curiosity		
Functional managers	**Central analysts**	**In-house analysts**
▪ Highly curious ▪ Use curiosity to oppose the BI data	▪ Highly curious by nature, ▪ Unable to explore their curiosity due to the time and target pressues	▪ Follow their curisoity to probe the data ▪ Attempts to triangulate feelings with opinions and BI data
Disproving myths		
Functional managers	**Central analysts**	**In-house analysts**
▪ Use of BI to disprove myths ▪ Use BI to disprove the data itself	▪ Use of BI to disprove 'intuition' and 'gut-feeling'	▪ Working in conjunction with functional managers to bust myths
Personalties		
Functional managers	**Central analysts**	**In-house analysts**
▪ Extroverts ▪ Highly reliant on communication and dialouge.	▪ Introverts and analytical ▪ Less interested in discussions	▪ Highly analytical, yet more open to discussions given their embedment in the evironment
Data manipulation		
Functional managers	**Central analysts**	**In-house analysts**
▪ Manipulate data often to tell a positive 'story'. ▪ Refered to this as creative data representation ▪ Highly reliant on in-house analysts for data manipulation	▪ Portrayed no interest in manipulating data ▪ mainly due to them being a corporate central service, therefore presented data as it read.	▪ Provide creative analysis for managers, depending on what was requested and with it being 'within reason' ▪ Especially for business cases. ▪ Managers very reliant of them

Table 6.2: Summary of 'Actors cognition' mapped across the research participants

6.4 Contextual complexity or heterogeneity?

The NHS is a large organisation that can be described as have a tall structure, being political and highly complex. The complexity of the NHS and the nature of this organisation is manifested in the way in which it operates, which directly impacts the relationship between individuals, groups of organisational actors, and departments. This theme was extensively brought to light by the participants of the research, particularly when they tried to identify the challenges associated with the effective use of BI. Due to a lack of standardisation and consistency, it was clear that the fragmentation and heterogeneity caused issues throughout the organisation. In the context of this research, this heterogeneity was a direct result of a lack of consistency across systems, data sources, goals and ways of working, as highlighted further in this section.

6.4.1 Disparate sources – '*We're comparing apples with pears'*

One of the challenges faced by the operational staff, was a plethora of systems were being used across the trust, which led to obvious issues around data quality, duplications, and the difficulty in capturing the most essential and relevant information. Although various systems have been introduced to collect data centrally, such as the e-Referral Service (eRS) in a bid to combine electronic booking, with choice of place, date and time for first hospital or clinic appointments, this was still proving to be a challenge as highlighted by central analyst, C.S highlights

'The aim is to get everything that comes through eRS to keep it on eRS, and if anything happens it needs to be rebooked by the, choose and book system and what this graphic showing is (points to screen), they are not necessarily doing that, it looks as though they are cancelling it off eRS and booking it outside of the system and it's quiet, which then leads to even more distance between us and what is happening in the wards'

Here, the central analyst highlights the incorrect way in which the systems are being used, which can lead to a further widening of the gap between their understanding and of what actually occurs within the wards. The fact that, although centrally driven initiatives and systems are in place, this still does not deter people within the departments and directorates from still using previous processes and older systems. To highlight the varying systems used, J.J also highlights:

'So we have the national database, Electronic Data Management System, PDFs because a lot of the things are in notes, various spreadsheets that people, other teams keep up to date, Lorenzo.. Oh, and the BEST system. But they don't talk to one another!"

This example from the Mobility and Specialised Rehabilitation Centre highlights that departments have a variety of systems that collect particular types of data, yet operate disparately and '*do not talk to one another'.* This could prove to be a challenge particularly when analysts are trying to capture a snapshot of the activities and operations within the ward. She also suggests that this is a problem across the trust: '*I think working with different systems in each departments doesn't help',* even though each department have various systems, the fact that each department across the trust are also using different systems makes it difficult to compare and gain an intuitive understanding of what is happening across the trust.

This also resonates with S.G, who provides a practical example of how such heterogeneity can lead to inefficiencies: *'I think one of the biggest problems within the NHS at the moment is that everybody is using different systems and even within the same department, we might have several systems let alone within the same directorate, let alone within the same trust'*

L.B, looks at it from a more macro level, and suggests: '*I am also aware that people would also say that we need to make sure that everyone is using the same systems and everything else. Particularly if you are comparing them with other hospitals and stuff like that,'* This therefore highlights that various organisational actors, particularly the analysts see the importance of having

data originating from a standardised system, not only across the trust, but the entire organisation, for a true reflection of how one is performing against trusts.

The homogeneity was a reoccurring theme not only in the context of the systems, but also in the ways of working. Central analyst P.S, highlighted: *'Even the way of doing things is different in the NHS! We all try to use Lorenzo as much as possible, some of the directorates do have their own clinical systems, so for example renal have their own clinical system, similarly ophthalmology also have a clinical system, and dental also have a clinical system, so there are clinical systems dotting around, but all the admin stuff goes on to Lorenzo, but how we are doing things is very fragmented and needs standardising, if we're serious about being paperless!'*

Proactive steps are being taken by the NHS in this regard, S.S highlights how the organisation is trying to centralise the data particularly given the paperless environment that the organisation looks to operate in, the coming years. He states: '*We try to centralise all of that, so that the coordination is staff are managing all our patients will get put in one big pot, so you should be able to just talk to one team to get everything organised in a cohesive manner..'*

This divergence is a real challenge for the NHS, and also for the analysts and functional managers who attempt to derive value from this data. Therefore, from a trust wide perspective, it can be argued that the fragmentation within the NHS, in terms of the ways of working, disparate sources and also the divergence in skills and abilities in using the data can be seen as some of the key challenges which inevitably lead to tensions between various organisational actors and contributes to some of the disputations emphasised earlier.

6.4.2 Disparate departments – '*Silo departments, silo mentality, silo people..'*

As though the disparate data sources and incompatible systems was not enough of a challenge for the NHS, it was also identified that the departments and services operated very independently and remotely, lacking communication and transparency. As such, this was having an adverse impact across the trust, leading to a lack of organisational learning and partial knowledge sharing and best practice, which also heightened tensions amongst organisational actors across various departments.

Such divergence between the departments can lead to departments and services pursuing their own goals and objectives, regardless of its wider implications. This can be seen when R.L discusses how the central analyst team operates*: 'I think it's different goals, different, they just want, they just after what the hospital cancellation rate is. They just want the numbers. That's what they want to do, they just want to come up with a number, it's not incorrect, what it is, people who do not have the expertise understanding wouldn't necessarily know what it's referring to, whereas I would be able to see past that and know that in reality it is a lot lower.'* Although both sets of analysts ultimately providing a similar service, their lack of cooperation, geographic difference and obvious disparity in their orientation results in a diverging focus and goals, which can be contradictory.

This is further emphasised by P.G who also has experience of working with both central and in-house analysts. He argues*: 'errrm, it's different goals I think. Next they would show the trust position, so they want to show the trust position so as trust what is the length of stay.. But that's meaningless! But that's what they are being asked, possibly by outside because no one, because people aren't asking our chief executive what length of stay is for a tiny bit of it, they are looking at it from a macro.'*

The differing nature of work amongst the analysts is reflected through the type of queries they are tasked with producing. While the in-house analysts focus on the local, environment in which their embedded, the central analysts operate both for internal directorate queries as well as trust wide reporting. Therefore, It is evident from the statement of Performance manager P.G, that

switching from the macro to the micro is difficult for the central analysts team, which is why they are not seen in a very positive light by some of the functional managers, as also highlighted earlier. However, the disparity and lack of transparency across the trust is further discussed by R.G, who outlines his frustrations at the organisation not learning and sharing best practices: *'It's about having the organisational memory that, in becoming a learning organisation and not relying just on one person's experience but bringing that into the way you do things. it's about taking that forward, and I think we really bad at that to be honest. I think we are quite bad at it. But that's part of it, because that's where it should be the experience of the organisation, not just one individual, regardless of who that may be.'*

It is evident here, R.G is critical of the NHS and its failure in becoming a learning organisation. Much of this, he argues is a result of individuals not disseminating their expertise across the organisation, to other organisational actors who operate in similar roles. Again, this can be attributed to the disparate and internal departmental focus, which, J.L further highlights: *'We're constantly trying to challenge the Silo mentality, people are so siloed, but I don't think we can blame them, there is a lot pressure, targets that need to be met'.* This silo mentality, which J.L believes is also a result of target driven performance pressures, is leading to a situation whereby resources and expertise is becoming increasingly fragmented, creating further detachment and isolation between organisational actors.

This was also recognised by central analyst, S.G, who highlighted the lack of communication taking place between the services: *'I think that is another big issue, that's services do not speak to one another.. but we seem to be reinventing the wheel in so many of the services, particularly around capacity and scheduling, err all the services seem to have their own spreadsheets and on methods for, for working out their capacity and the contract monitoring going forward, there is no unified system out there so they all do their own thing and, it would work much better if we managed to get everybody together*

working and even sharing knowledge, that must be the way forward and then to try and unify the systems'.

As a Central Analyst, based in the Central Performance and Informatics team, S.G deals with queries from across the trust, therefore is able to see the extent of this fragmentation from a wider context. He feels that the services would benefit more from sharing knowledge and their practices and that there should be a drive towards standardising how they operate. As established in the earlier sections, cross-departmental contestations between various organisational actors is common, therefore this fragmentation across the trust adds another layer of complexity, which hinders communication and articulation and inevitably contributes to the tensions between the departments.

6.4.3 Organisational Culture – *'Data-driven, everything has an 'e' in front of it here'*

The organisational culture of NHS is inherently seen as playing a major role in the way things are conducted within the organisation. The findings have alluded to the bureaucratic, politically-charged and data-driven fabrics that the organisation's culture is built on. Therefore, it is inevitable that the culture of the NHS plays a significant role in helping explain some of the challenges highlighted by the participants of this research.

The discussions from the previous section indicate that the organisation as a whole is committed to being data driven, as also reflected by the long-term strategic vision of the NHS, by going 'Paperless by 2020'. However, it is apparent that while the organisational actors, particularly the functional managers are expected to underpin their decisions by data, the organisation generally is struggling to garner value from this data. When discussing the complexity of managing operations within the services, services manager, A.H highlights:

'It's due to all sorts of thing, such as lengths of stay, patient behaviour, clinician behaviours and then you add the unstructured elements, and having worked in other organisations, I think this is a data, we are very data driven in this organisation. I think it's because of cultural, (pause).. That's my interpretation at least, but there are lots of things that numbers won't tell you'

The organisational culture therefore is described here as being heavily reliant on the data, however the manager outlines that the data does not necessarily tell you everything, something often reiterated by functional. Therefore, it is argued that the data driven organisational culture of the NHS can be considered as a contributory factor in indirectly a) creating dissonance between managers and analysts, b) in impacting power dynamics within the organisation. Supporting this further, R.G emphasises the NHS wide data initiatives and the challenges associated with it when he states: *'there is a trend in the NHS through, again nationally driven directives by NHS , NHS, everything has an 'E' in front of it, e-records, e-prescribing, all the sort of stuff. So we are heading more and more towards this, yet don't have the collaborative ways of working Figured out yet'.* Therefore, it is important to identify the role and correlation between the data driven culture and the lack of convergence between various organisational actors, particularly the functional managers and the data analysts. Furthermore, the role of hierarchical influence was also highlighted as being significant, as failure to challenge the perceptions of the executive management was also considered a norm, particularly at the lower, operational levels of the organisation. This can be seen when P.G highlights:

'Culturally, there is definitely, (pause), resistance to challenging executive team on assumptions about services, so if people say things in our executive meeting about the service, I have seen it when people from that service know what the exec members are saying is wrong, but they don't, they don't, and they could even show some data to show that, but don't they don't feel able to challenge that.' This highlights the influence of senior organisational actors within the NHS, and offers further insights into power considerations and

emphasises the influence of the tall hierarchical structure in which the NHS operate. Additionally, General manager T.H, highlights:

'My view is organisationally, there is an expectation that if you were working on, you work in the services you have targets to hit, there's an expectation that you've got to show that you've done something, and I kind of agree with that, but organisationally, there is definitely an expectation that you try and find a positive story'

It can be argued that much of the 'data manipulation' and 'gaming' by functional managers discussed earlier is a direct result of the expectations within the organisation of accomplishments and success stories, which from a power dynamics perspective, vastly favours the analysts, as their skills are often fundamental in ensuring that data is presented in such a way, which promote 'achievements'. Interestingly from the narratives, it was evident that many organisational actors referred to the term 'expected', 'We're expected to' 'you would be expected to', consequently, one may argue that this implies the expectation of the organisational actors through the eyes of the senior board, such as the executives and operational directors. This was evident on many occasions, with some examples presented here:

'You're expected to come back with an answer, or solution, regardless of whether you had all the information or not' – Service Manager, A.H

So my experiences as a service manager was, kind of, you are expected to come up with the answers like that, so any time for any sort of thought around decision-making and trying to get some information that might help you make a sensible decision seemed limited. – Performance Manager, P.G

'There certainly is an overarching expectation that we are able to deliver, at least 95% of the planned capacity'- General Manager, J.W.

You know as with every other service in the NHS the expectation and demand is way outstrips what we could possibly hope to achieve. So you know, a lot of

what I do at the moment as demand management and prioritisation. – Informatics Enterprise Architect S.S

This accountability and answerability is resultant of the nature of operations within the NHS and also affirms the role of the organisational hierarchy and the seniority of organisational actors operating within it, thus implying the significance of 'process power' within the organisation. More so, these expectations are not solely enforced by senior management of the NHS trust, but are also driven by patients and other stakeholders of the NHS. Furthermore, S.S also deliberates on the organisational structure and believes in addition to the culture, the size, scope and complexity of operations within the NHS are also critical factors:

'I think there is something in this organisation in its culture and history, that we don't like being told and, you know, without a minuting it too carefully, I think there's something around the organisation potentially being so big that it's too far-removed from operational management, so the executive care aspiration of making things happen of course, it just, has to come down from so many tiers, that I actually never happens on the ground! … it's just a, it's a theory.' He believes that the tiered organisational structure and the breadth of operations within the NHS makes it very difficult to manage in a coherent and standardised fashion.

Although there has been extensive discussions relating to the data driven nature of the NHS and how the organisation in the coming years will continue to collect more and more data, from a practical context, it was revealed that access to this data is not always readily available. R.G attributes this to political factors, whereby the organisation only makes information available which it deems appropriate and also can and does withhold data, he argues: *'so the first thing is access to data, is, is difficult. I don't have, what I would consider to be free access to data. In the sense that I don't have data at my fingertips, information which I feel I need all the time, to do my job effectively. And that's a big problem. The reasons behind that are manifold, some of it is political, small peak gatekeeping… In the terms of that control information, you know*

knowledge is power, control information, control what people say. So that's part of it, part of it is technical, around the skills'

Although there is a real aspiration and push for a data-driven culture, it can be stated that functional managers, who have decision-making capabilities and authority, may find that they are either relying heavily on their analysts, due to deficits in their technical, analytical skills, or that they do not have 'free access' to all the data they may require, due to political factors. In both instances, it can be argued that the power dynamics are certainly impacted as a result of this data driven focus, further reducing the influence of operational managers.

6.4.4 Time and target pressures - *'Asked to do more, with less'*

The size, scope of operations and nature of the organisation has led to many pressures in recent times. The NHS has faced many challenges which are regularly aired in the mainstream media, particularly during seasonal variations, such as winter pressures and many other aspects of their service. Therefore, it is widely accepted that internally, the organisation is stretched for resources and in recent times found to be more reactive in their approach as oppose to being proactive. Nonetheless, the findings revealed some of the challenges and dissonance discussed earlier were both direct and indirect consequences of the NHS's commitment in trying to meet performance targets and time constraints, due to increasingly internal and external pressures and stretched resources.

Central analyst, C.S elaborates on the target and time pressures of her role and others within the central analysts team: *'Yes, it's quite handy to know how directorates are working and being able to highlight that, I think sometimes we don't have time to do it, it's good to have that curiosity and say right this is that the logic should work, but being actually able to delve into this, you know this logic might work 99% of the cases, but what about this 1%?'*

What distinguishes the in-house analysts from the central time is their knowledge and contextual insights, which allows them to, as discussed in the previous sections operate more intuitively and creatively to the extent that they are also able to assert influence due to their analytical expertise and contextual knowledge within their operating environments. It is clear from C.S that time constraints renders it difficult for someone in her role to delve into how directorates and wards operate and as a result they are unable to provide a more personalised and ward specific service.

S.G also emphasises the target driven nature of his role: *'So my role is specifically to do as many jobs as I can and get the information, other members of my team may have slightly more analytical role, but my role is to given the circumstances, is to get as many of these jobs done as possible.*'

As well as the central team analysts, the functional manager also operate in a fast-paced environment in which time pressures and meeting targets are key challenges they face. However, it is evident that in such cases, the in-house analysts can facilitate the managers in their data queries and therefore offer more support, in more of a timely manner. In contradiction to the central analysts, M.B, states: *'I feel like managers are usually quite eager, when I give them work, they usually try looking at it in other ways.. But like I said there is the sort of time aspect, with that and how much time they have to look at data in more depth, which is I guess where I would come in…'* Therefore, this highlights that while the trust as a whole is confronted with time pressures, the central analysts are more adversely impacted, due to the nature and scope of their role. Resonating with this, in-house analyst, R.L is also found picking up from where the 'central analysts left off' due to their stringent deadlines: *'I'm sure they're busy, I wouldn't say they're not, but then as a result I'll end picking their stuff up.. So this is where my role comes in, but sometimes I feel like, it is duplication because you know, its repeating work, which often they'll do wrong!'*

Highlighting this further, central analyst, P.S raises the fact that although there are internal discussion of implementing predictive analytics in the near future,

he believes that people do not have the time to learn the tools, nor the skills to effectively operate them. Which highlights that both the skills disparity and time related challenges are still potential challenges the NHS will face in the foreseeable future:

'That's one of the things we don't have in the organisation, a proper BI system which can help us minimise breaches through predictive tools. But the difficult part is, the difficult bit is people say they want stuff, but when they have it you realise they don't have the time to use it, or they don't have the skills'. The tensions between the central analysts and the functional managers were also evident in another instance when central analyst, P.S criticises the functional managers, but refrains from elaborating further:

'I think it's a lack of time to, because we're so pressured. We just don't have the time to do more stuff (for managers) It's easy isn't it?, For somebody to give you what you want exactly how you want it, then for you to… but from my perspective if I was managing the service, I'd want the data, because I will define the patterns and things like that, I just would want somebody to give me that. But that's just me, and am not managing the service either am I?? (LAUGHS)..'

P.S argues that it requires limited if any effort requesting information from his Central team, although he cuts short when highlighting that they send information to managers as requested, 'then for them to…' based on the previous discussion, it is highly likely that here, P.S was referring to the lack of actual use of the information by the functional managers. He continues by stating that as a service manager, he would request the information to identify patterns, as such implying that the current functional managers do not use it effectively. Again, the tensions here can be attributed to the skills disparity and the time pressures. This was also expressed by another member of P.S's team, J.R, who shared similar sentiments: '*the directorate would say they want one thing and actually when you give it them they actually don't want it at all. I mean there's even reports now on the website, but it's easier to pick up the*

phone and say can you give me this report?, …. But it's all there, I don't have time to do that?!? (Sarcastic tone)..'

The central analysts are of the opinion that it is rather convenient for functional managers to request of their services, with little accountability of whether they use it or not, thus taking up their valuable time, with little impact achieved as a result. However, based on the previous discussions it is evident that the functional managers do exercise caution when using operationalising information sent by the central team, as it may not either be fit for purpose, due to limited contextual insights, or may be using the data, only to 'stress test' their personal gut-feelings. In addition, various central team analysts openly confessed limited articulation taking place between themselves and the functional managers, due to the pressures of their role, as stated by C.S:

'Obviously my own curiosity, does come in every now and again and I'm interested in why somebody has asked for a particular set of data, but unfortunately I really don't have the time to delve into it too much'

The implications of the time pressures are that the central analysts are unable to maximise the usefulness of their BI generated reports for functional managers, therefore use BI more for reporting purposes, rather than supporting decision-making making. This relates to the earlier challenges and discussions, which identified the central team as working through tasks list. C.S outlines:

'Being able to have that time to look, that's the real barrier sometimes... I think we would become more knowledgeable and intuitive, if we weren't so sucked for time, because we're just so busy all the time with the work. And it's like you don't really have time to reflect on what you have done and necessarily be able to hone your skills in what you have learnt in one, so you might just pinch some code of the Internet, and you know it worked really fantastically, but you don't have time to digest what the code is doing it just works, and just move on. I don't think we have the time to internalise it we just move on It's almost like a vicious circle really because you can't it takes more time perhaps next time.'

Therefore, building on the discussions highlighted previously, the central team use BI non-intuitively, with limited insights into the purposes or the impact of what they produce for the functional managers, as a result this further alienates the functional managers and creates tensions, which eventually leads to the contestations and the ‘us and them’ mentality highlighted in 6.2.1. The disputation and incongruity between service and managers and central analysts can also be attributed to the time constraints and performance pressures, particularly as the central analysts prioritise their tasks and performance according the jobs that come through the central email system and not according the specific needs of a particular directorate or for the tailored requirement of the functional managers. Table 6.3 provides a summarised account of the key discussions from this theme.

Disparate sources		
Functional managers	**Central analysts**	**In-house analysts**
▪ Inconsistent metrics ▪ Lack of Org learning ▪ Difficult to compare their performacne with other managers from different departments across the trust	▪ Complaints against a number of the systems and plethora of data sources ▪ Leading to inaccurate and inconsistent use	▪ Highlighted importance of having consolidated data sources ▪ However were less concerned with trust wide reporting
Disparate departments		
Functional managers	**Central analysts**	**In-house analysts**
▪ Lack of interactions with other managers in the trust often leading to diverse ways of working and inconsistency across the trust	▪ Disparateness between both central and in-house analysts ▪ Further emphasises high fragmentation within the NHS	▪ These analysts are valued within their wards and clinical care groups due to corporate and ops depts divisions
Organisational Culture		
Functional managers	**Central analysts**	**In-house analysts**
▪ Highlight the top-down approach of management and the data-driven culture ▪ Top-down paperless push has led to managers being more reliant on analysts than previously	▪ Data driven decisions have made the central analysts more busier, with endless enquiries from a variety of sources.	▪ Benefit from senior manager support and legitimation ▪ Emerge as highly influential due to the data-driven culture, ▪ Their technical and contextual skills add value
Time and target pressures		
Functional managers	**Central analysts**	**In-house analysts**
▪ Operate in a highly busy environment ▪ Have little time to 'learn' or engage with BI data ▪ Often relying on their personal intution and gut-feelings.	▪ Significant impact on how BI technology is enacted by the central analyts. ▪ Resort to reporting with little insights and personalisation due to the nature of their role	▪ Have less time and target pressues ▪ Benefit from more creativity and freedom to enact BI more personally to contextual settings

Table 6.3: Summary of 'Contextual complexity' mapped across the research participants

6.5 Institutional Knowledge – '*BI isn't just the ability to provide information, but to understand the context in which it sits'*

A major theme that was prevalent throughout the participant interviews was categorised as that of 'institutional knowledge'. This refers to the local, contextual knowledge that was generated, shared and disseminated within the various services and wards within the NHS trusts. This contextual background knowledge was seen as being pivotal in operationalising and making usefulness of the BI data for decision making purposes.

The institutional knowledge in this case was built-up through the unstructured discussions and therefore manifested as unstructured data, which was generated through conversations within the wards between various organisational actors, such as the admin team, the clinicians, the consultants, the functional managers and most importantly the in-house analysts. Furthermore, the processes, ways of working and procedures also informed and contributed towards this local knowledge. The battle for the power dynamics between the functional managers and the analysts was won and lost through the highly valued, contextual detail of operations within the actual environment itself. As such it was the local in-house analysts who were able to leverage advantage and influence through their ability to relate to both the analytical aspects and the localised contextual knowledge.

For instance, service manager A.H highlights the significance of having local knowledge and of what occurs within the wards, due to the complex, and often chaotic nature of operations, which is not reflected merely in the data. She discusses the importance of this institutional knowledge for the analysts who are tasked with providing actionable information for decision-making. She states:

'*We probably had a business analyst in this care group for maybe around three years. Before that, I think there would have been a heavy reliance on the central team, but you are then.. We are a large trust and it would be great if we could share more centralised resources, but sometimes you need*

someone who knows a local context and it is, available when you need them to be available. Whereas, if you are putting in a request for information services that is like a one-off building of a report, you join the queue and you have no influence over that, unless it becomes a priority and someone escalates that, whereas with the in-house analyst, I could go down the corridor now, and ask. And it might not be done today might not be done this week, but we would continue to have a joint dialogue. The central guys are good, but it is that sort of local knowledge and understanding and influence and they are a corporate resource, and they need to respond to things that are famous for everybody I suppose so, there is lots of national reporting that they do on our behalf with no, we don't need to, to sit and have a conversation about what our 18 week performance is, it is what it is, they can turn it off.'

Here, A.H highlights how the ability of the in-house analyst to understand some of the technicalities from within the speciality plays a major role in the joint dialogue between herself and the analyst. Resonating with the previous section, she highlights how the central team are inflexible and prioritise their tasks according to wider issues that are being promoted on more of a national scale, instead of making ward specific challenges their priority. The role of contextual information is further highlighted when N.A states:

'So business intelligence just isn't the ability to provide information, but to understand the context in which it sits, and then apply all of that in the sort of holistic way, you need to layer on the other things onto that, so for me, business intelligence is information within its environment. And then how that applies within the business setting that you are in.' This service manager is of the view that BI in its very nature should be related to the business settings in which it is applied, thus further emphasising the role of institutional knowledge for successful BI application. It seems that the organisational actors acknowledged the importance of contextual insights from a BI use perspective for a variety of reasons, for instance, Information Manager, S.A mentions any service which deals with 'people and patients' is unsteady, inconstant and varying. Therefore, through acknowledging contextual, environmental insights, allows one to account for changes which inevitably would remain

unnoticed in data. He states: '*I think, through time, or through changing context, things are more or less important in different times aren't they? If you're in the environment, you know exactly what's changed, whereas centrally they might not flag or pick up on it'.*

R.G also stresses the importance of being able to identify step changes and ensuring that this is accommodated as part of the way moving forward: '*So I would expect to see that change. To an extent, but if you don't know that, then you don't know why there's been a change.. So if you don't know that background, then the changes are out of context, and makes no sense. So, you have to understand the context behind the data I think to help you ask the right questions and help you get to where you try to go with it.'*

Therefore, the ability of recognising changes in the environment and having the knowledge to apply this in terms of how this may affect the services within wards can then be supplemented and incorporated as part of the BI generated information to make more meaningful sense of the data. C.S who is currently an analyst for the central team reflects on her previous role, where she was a business analyst within a directorate, upholds the sentiments of the service managers and outlines:

'I remember a name called Val, one of the managers, and she would come and sit with me and go through everything with me. And I would get a real understanding of it. Whereas I do feel very much removed here perhaps, I don't know, like it can be a bit, it can be a bit difficult but at the same time you can still answer those questions if you need to, perhaps not as forthcoming.'

This not only highlights how the analysts are able to internalise vital information which can prove highly benefit for their analyses, but also outlines how the analysts are able to embed themselves as part of the team and build relationships with colleagues within the ward, as such reducing the obscurity traditionally associated between both groups of actors. As such, this projects the in-house analysts as being more competent and knowledgeable than the central analysts, which can impact power dynamics between analysts as a group, and between the in-house analysts and their colleagues within the

wards. The importance of relationship building and bridging gaps was repetitively highlighted by the deputy service manager, R.G, who emphasised the real need for the functional managers and the analysts to work in harmony and in unison, particularly given the data driven future direction of the organisation. He states:

'I think it's an important relationship and it's increasingly becoming more important, the link between operational managers and analysts because, it's the rate at which data and information is proliferating in healthcare. As, as data proliferates, and were used to things like mobility and mortality rates, they've been around for a long time, we get that. But more and more data, more and more IT systems, everything is information-based, which is either a variable if we ask for it, or what we have been managed by. So, the role of the data analyst is becoming is increasingly... so that, that dyad, that two-way working has to be absolutely fundamental.. so the analysts that are based in the directorates are only semi-integrated, and they are often a contested resource. That is one of my big bugbears. We really require more of them if we are to leverage value from all this data.'

R.G again refers to the importance of the in-house analysts if the organisation as a whole is to reap the benefits from the data-driven culture adopted by the NHS. Importantly, he emphasises the dyad and the two-way working between the functional managers and the analysts as being fundamental in achieving this. However, as established, the reality could not be further from the truth, as it is also apparent that due to their multifaceted skills and expertise, the in-house analysts have the ability to exert influence within their operating environments, and thus has diluted the legitimation of functional managers. Nonetheless, when compared to central analysts, it can be said that the in-house analysts and functional managers share a more transparent and open relationship.

Analyst, J.J, also highlights advantage of her working as an analyst within the department allows her to see the data in a different light by understanding the key processes within the department:

'Working as a data analyst, in the department that is in the environment helps me massively. Hugely! if I didn't work in the environment, I wouldn't know who to ask for certain things, and just being in the environment itself allows me to understand the process behind something, which I can factor in within my analysis.. And it's widely accepted in our world that people don't ask the right questions, so when you sort of have been in that environment for a while, you get a good feel for whether they are asking the question that they want answering.'

Therefore, it is evident that J.J firmly believes that by being in the environment allows you to answer managerial queries more effectively, particularly given that managers may not necessarily ask the right questions when they are wanting to explore something, as also highlighted by the other analysts, including C.S and P.S.

Furthermore, P.S as a central analyst adds to this discussion supporting the sentiments aired by others and suggests that if he has both the time and subject matter, he is able to go back to the functional managers and explore options with them however, he argues that if he doesn't have either he's simply provides data, regardless of how useful it may or may not be to the managers;

'If have got time, and I know the subject matter, and might say something like, okay this is a question that you have asked, this is the data you've asked for, this is why I don't think it tells you what you thought he did, and this is what I think we tell you what you wanted. So, I'll try answering the question as fully if I've got time, sometimes I don't know the subject matter, and sometimes they don't have time, in which case they just get the data they ask for.'

Reverberating with the previous discussions, this highlights the limited impact of BI use across the services and also emphasises how central analysts are bound by time constraints and target driven prioritisations, which is often reflected in the overall quality and relevance of the data they provide. However, through the narratives, it has been established that the central analysts generally lack both time and subject knowledge, therefore this further highlights the importance of the institutional knowledge from a BI perspective.

Therefore, it is due to these factors that the functional managers favour a more localised, in-house resource. R.G posits: *'What I would like to see if we had analysts who are embedded more in our directorates, I don't expect them to be able to, kind of do, my job and getting to the nitty-gritty, I do think it's important for them to understand who is using the information and how they're going to use it.. What format they want it in, I would think you get that when you work with people constantly, which we don't have enough of. So that's what I would like to see more of.*

As such, R.G emphasises how the disparity between analysts and managers are underpinned by differing perspectives and focuses that essentially act as triggers for contestations and disagreements, which can potentially be overcome through more in-house analysts taking up positions within directorates. From a more senior position, S.A is also in agreement, suggesting: *'And that's when you get operational managers say that 'this data is useless, why are they sending me this, I can't do anything with it' and the business analyst will say, 'he's asking for something completely random, I need much more detail, what's the key identifier, what is your inclusion criteria, what is exclusion criteria, what's your timeframe, how are you going to structure this?..'*

The complexity and layers of the NHS have to also be appreciated when emphasising the necessary 'Institutional knowledge' for BI use. Accordingly, S.G, though a central analyst, who previously highlighted his focus of 'getting jobs done', with little interest in providing a more analytical service, mentions that experience is imperative in order to be effective within the NHS, and breaks down the areas of NHS expertise he feels are essential.

'You might look at the results of a report that I have written and think, 'that does not look quite right', and I guess that is purely based on experience I don't think the way to learn that it would just be based on experience. A - experience with data in general in any context, but B, NHS experience. So, and then C, experience of a trust that you are in. So quite often, roles within

this trust ask for NHS experience, which is desirable or even essential. I would say the more micro your knowledgebase, the better it is.'

Clinical analyst, S.P discusses managerial influences and highlights how this was previously exercised with analysts: '*I think historically, it (influence) lied with the managers, whereby the analysts can get wheeled out as and when required and then put back in their box. But with.. you know the movement towards going paperless, the analysts, especially those in the directorates are becoming more and more important.'*

However, the drive towards going paperless and recent digitisation focus within the NHS is seen to have shifted the influence in favour of the in-house analysts, who are regarded as valuable imbedded assets within the wards and services. In order to explore how the use of BI is influencing power dynamics from within the context of directorates, the Associate director of operations, S.A offers some interesting insights into internal influences within the services and how he, as an organisational actors of high seniority views this:

'An example could be, you could ring me up as a junior doctor wanting some advice, and you could say that I have seen such and such patient, these are the parameters, these are the details that are coming through, now based on what you're telling me, without clapping eyes on the patient and putting hands on the patient, I could say that sounds like this or that , but without physically seeing the patient, and understanding the bits going on, I can't give a conclusive diagnosis over the phone. Similarly, what I can draw from this example is, the analyst is sat behind the screen and seeing it, without physically being there, but the ops manager is in this case the clinician on the shop floor, clapping eyes on the shop floor really understanding what the data is revealing, that's the important part. Unless you're an internal analyst, I'm 9 / 10 going to back the Ops managers'

It is evident that as director with extensive organisational influence and organisational power, if he is presented with scenario where he is having to pick between an analyst or functional manager, he would base a decision in favour of the manager, due to their contextual knowledge and ability of

knowing what is happening in the wards and services. Conversely, he emphasises that if such situation was to arise between functional manager and an internal (in-house) analyst, he would favour the latter. This can be attributed to the in-house analysts multi-faceted skillset, therefore also allowing them to gain legitimation and 'influence without authority'.

Therefore, this ability of influencing decisions is imperative and demonstrates how the in-house analysts are shifting the power dynamic relationships within their environment through becoming more influential beyond their scope, through gaining the support of superiors. The significance of this is further highlighted when R.G discusses the importance of being able to convince the senior directors when disagreements occur between themselves and the analysts. He mentions: *'Would I be happy to challenge the business analyst? the answer is yes. But that still is not an isolated decision, I would be going to my clinical director and having a conversation with them and things 'Steve', the data says this, the analyst says that. I think you and me as accountable officers for this directorate, we need to agree on what a decision is, and that can be yes the data says this, but we are going to do this anyway for the reasons, which is the ideal situation, or actually the data this challenging what we thought so we need to do something different.*

This shows that when functional managers are not convinced by what the data is indicating, they may choose to deliberate with their superiors, in order to try influencing a decision in their favour. Interestingly, it can be argued that by stating *'I think you and me as accountable officers for this directorate, we need to agree on what a decision is',* reflects the persuasive rhetoric the functional managers ploys in order to convince the director that they must decide on a decision together, which reflects both of their best interests. Accordingly, in a situation whereby the director is having to choose between a functional manager, who is well acquainted with the operations within his service and a central analyst, who operates remotely, away from the environment, it is highly probable that the functional manager would be successful in having the decision ruled in his favour. However, as highlighted earlier, through the ability of knowing both contexts, it is more likely that the senior directors would

support the decisions and version of events presented by the in-house analysts.

Overall, the participants, particularly the functional managers have revealed a strong desire for in-house analysts as opposed to central analysts, predominantly due to the institutional knowledge which the former are able to effectively use. This contextual appreciation offers more tailored and personalised insights into the operations within the directorates, particularly as the analyst has the ability and skill-set to supplement the data with the contextual insights. Alternatively, one must also argue that this 'favouring' of in-house analysts over central analysts by the functional managers is two-fold. Firstly, as the in-house analysts are able to offer a much more focused, personalised and appropriate insights for their managers, when compared to the central analysts. However, it must also be noted that the in-house analysts are able to significantly influence the outcomes of decisions and also gain legitimacy and support of senior managers due to their multi-faceted skills. Thus, the resource power that the in-house analysts possess enables them to influence without authority and as such, become more valuable and dominant within their environments through their ability to alter other people's perceptions of a situation, such as what decisions to take. Table 6.4 provides a summarised account of 'Institutional Knowledge' mapped across the research participants.

Institutional knowledge		
Functional managers	**Central analysts**	**In-house analysts**
▪ High degree of instituitional knowledge, made up of operational experience	▪ Limited institutional knowlesdge ▪ Benefit from have a marco, wider view of NHS operations across the trust. ▪ Mainly analytical	▪ High instituinoal knowledge as well as analytical skills, making them highly valuable to their functional managers as well as senior management

Table 6.4: Summary of 'Institutional Knowledge' mapped across the research participants

6.6 Conclusion

Qualitative thematic analysis was used to analyse the data with the aim of exploring the research propositions, while also anticipating unexpected findings to emerge from the data (Klein and Myers 1999). The analysis process consisted of data transcribing, coding and analysing. The data was analysed using NVivo software in a flexible manner, whilst attempting to interpret key aspects of the research (Boyatzis, 1998). Data Familiarisation was attained through repeatedly reading the interview transcriptions for each participant. Any significant themes that emerged would be noted within the NVivo software, with the aim of trying to uncover similar meanings and patterns from within the data. The data which shared similar meanings were then categorised, which eventually led to identification of broader themes across each of the data sets which are summarised in Table 6.5

Themes and Sub-themes	Brief description of sub-themes	Frequency of reference to the sub-themes
Theme: Social pressures	This theme highlighted the tensions and disputes that occurred between various organisational actors as a result of the use of BI.	
a) Functional managers and Analyst disparity	a) Contestations resulting from divergent skills-sets and responsibilities between functional managers and (mainly) central analysts	85
b) Analyst incongruence	b) Conflict between central analysts and in-house analysts resulting from differing approach and BI application underpinned by macro vs micro focuses	45
c) Skills disparity	c) The widened skill gap between fortunately managers and analysts often lead to a disjointed, fragmented and uneasy relationship	37
d) Data vs intelligence	d) The trade-off between data and intelligence, whereby it was revealed that the BRI generated data was having limited	31

	impact due to over-emphasis on the data, organisational culture, lack of transparency and actionable insight	
Theme: Actors Cognition	This theme highlighted the disparate manner in which the BI was being used between the various organisational actors, as such this also impacted the overall dynamics within the trust	
a) Intuition	a) The functional managers mainly used their personal intuition and gut feeling to disprove the data, whereas the central analysts lacked intuition due to limited insights into the context. The in-house analysts through their analytical understanding and contextual knowledge were best placed to make intuitive yet effective decisions.	65
b) Curiosity	b) The use of BI prompted curiosity, though differently between the actors. While the central analysts had limited time to explore the curiosities, the in-house analysts were best placed to exercise more effective use of their curiosity.	38

c) Disproving myths	c) The functional managers will be seen to make extensive use of BI not for decision-making purposes, but in order to disprove myths and false beliefs populated in the wards. The BI data was also used in order to disprove the data itself.	27
d) Personalities	d) The functional managers revealed that the analysts were introvert by nature and therefore struggled to articulate and effectively communicate the BI info	43
e) Data manipulation	e) The functional managers who had a good relationship with their in-house analysts was seen to manipulate the data in order for it to reflect a positive, successful story	21
Theme: Contextual factors	This theme revealed the complexity of the NHS as an organisation which was predominantly a result of the fragmentation and lack of standardisation across the trust as a hall	

a) Disparate sources	a) It was evident that there were various data sources, both structured and unstructured, across disparate systems which contributed to the complexity	27
b) Disparate departments	b) The departments operated in a silo manner, which led to a lack of organisational learning, limited knowledge sharing and also enhanced tension between various departments	32
c) Organisational culture	c) The organisation is inherently political, and is strategising to become increasingly reliant on the data, those providing further influence, particularly to the in-house analysts	44
d) time and target pressures	d) Due to the performance pressure, the trust was often required to do more with less, thus also impacting the quality and appropriateness of BI use across the trust	47
Theme: Institutional knowledge	Through this dominant theme, it was evident that in order for the BII data to be used effectively	105

	and appropriately, the need for it to be supplemented with the institutional knowledge was essential and Paramount. Due to the local disposition, the in-house analysts were able to use both the analytical skills and they local contextual know-how to influence and impact the power dynamics within their wards	

Table 6.5: Identification of thematic themes and sub-themes

7.0 CHAPTER 7: Discussions

7.1 Introduction

This research set out to explore the interactions resulting from BI use between key BI users. As such, this research contributes further to the path paved by Shollo and Galliers (2016) through providing power consideration insights uncovered due to the use of BI by organisational actors within the NHS case context. Furthermore, the findings from the previous section also highlights the extent and nature of discussions that occur between various organisational actors during BI decision-making processes. As such some interesting findings have come to surface following the in-depth analysis of the 30 participants of this research will be discussed in further details in this chapter. The chapter will provide insights into the revised conceptual framework, whilst also presenting detailed discussions relating to the tested propositions of this research.

7.2 Revised conceptual framework

It was evident that the conceptual framework achieved its role in helping to tease out power dynamic dimensions, whilst also unravelling the disparate way in which BI is being used by divergent set of organisational actors within the NHS. The proposed Power Enactment Conceptual Framework applies dimensions of the enactment concept to help establish how BI is enacted by various organisational actors, whilst also drawing on multi-dimensions of organisational power sources (Hardy 1996) to gain an insight into the impact of BI use on power dynamics within the organisation. Therefore, this framework helped identify the divergent ways in which the central analysts, in-house analysts and functional managers were using BI as part of decision-making processes, whilst also understanding the implication of this on organisational power.

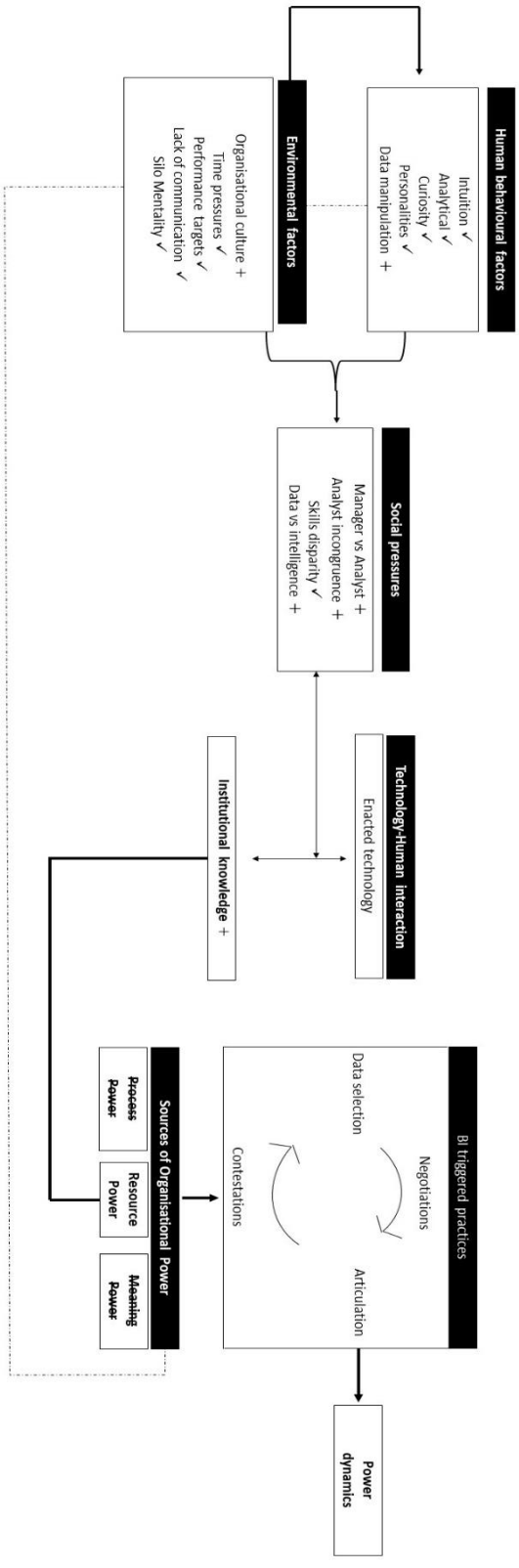


Figure 7.1: Refined power enactment conceptual framework

7.2.1 Revised Human behaviour factors

Understanding the role of human behavioural factors in the BI decision-making process is important, particularly given its role in also influencing how BI is enacted by the organsational actors. how to highlight. The following Tables maps the key area of literature / the conceptual framework with findings from the research:

Human Behaviour Factors	Demonstrated in Literature	Case study findings
Intuition	✓	✓
Curiosity	✓	✓
Personalities	✓	✓
Personalities	✓	✓
Analytical	✓	✓
Other: Data manipulation	×	✓

Table 7.1: Revised human behavioural factors

- ***Data Manipulation***

Following the data analysis process, the revised conceptual framework includes the additional construct of 'data manipulation' for human behavioural factors which impacts the way in which BI is used for the organisational actors. This construct was not considered in the initial framework, however it placed emphasis on the extent to which functional managers would rely on the in-house analysts to tweak and adjust data Figures to reflect, either better performance or for the purposes of case study justifications. Accordingly, it

was this activity in which the managers relied heavily on their in-house analysts for, thus making them highly dependent and reliant on the in-house analysts, which gave the analysts more leverage and influence.

7.2.2 Revised Environmental factors

The environmental factors have largely been overlooked from BI decision-making contexts within the extant literature. Accordingly, this research took into consideration the role of environmental factors commonly associated with the healthcare and other sectors, in impacting BI decision-making. The following Table maps the literature with findings from the research:

Environmental Factors	Demonstrated in Literature	Case study findings
Organisational culture	×	✓
Data sources	✓	✓
Time pressures	✓	✓
Performance targets	✓	✓
Lack of communication	✓	✓
Silo mentality	✓	✓

Table 7.2: Revised environmental factors

- ***Organisational culture***

The revised conceptual framework also acknowledges the additional construct of 'Organisational Culture' as part of the environmental factors which affects how BI is used for the organisational actors. This construct was not considered in the initial framework; however, it is evident that the culture of the

organisation played a role in how people actors would adopt and utilise a technology, such as BI, particularly given that the deployment of BI was part of a wider, national strategy. Although this top-down approach favoured the in-house analysts specifically, due to legitimation they were able to secure, the political and data-driven culture was seen to also have isomorphic implications, whereby the actors would feel obliged to use data for decision-making, regardless of skillsets or experience.

7.2.3 Revised Social Pressure

This research established the relationship between the environmental factors and human behaviour factors, whereby factors such as performance targets and time constraints directly impacts how the actors would behave and conduct themselves. For instance, the time and target pressure often led to the central analysts using BI as a merely reporting tool, with little insights. Or how the lack of communications also affected the perception of actors across different departments. This led to what is described as 'Social pressures' which manifested as a result of the combination of environmental factors and human behaviour factors. The following Table highlights these constructs from the revised conceptual framework:

Social pressures	Demonstrated in Literature	Case study findings
Manager vs Analyst	×	✓
Analysts incongruence	×	✓
Skill disparity	✓	✓
Data vs Intelligence	×	✓

Table 7.3: Revised social pressures

- ***Manager vs Analyst***

It was clear that the human behavioural factors and environmental factors led to contestations and disparity between analysts and managers, largely as a result of their varying skill sets, responsibilities and motives. This was particularly the case between the managers and the central analysts, who due to their restricted time scales, failed to provide sufficient, actionable insights for managers to act on.

- ***Analysts incongruence***

It was revealed that there was also disagreement and tension between the central analysts and in-house analysts, largely as a result of the differences in how they enacted the BI technology. The in-house analysts through being in the environment were able to supplement their analytical findings with the local, contextual details which would on occasion oppose the objective, analytically driven, insights from the central team. The inability of the central analysts to provide relevant insights was widely acknowledged across the Trust, therefore making the in-house analysts more valued and influential.

- ***Data vs Intelligence***

The managers were often seen to criticise how BI was used, and cited their disapproval of the insights generated from BI. There was a consensus between the managers that the BI tools produced very fancy data but offered little intelligence. Much of this was attributed to the lack of analytical skills of the functional managers, who were unable to make sense of the data and therefore would not fully reap the benefits of BI generated outputs, further causing tension between themselves and the analysts. Accordingly, the analysts also pointed out that the managers would request incorrect data when wanting to query a particular function or operation, thus the inability of converting data into intelligence through BI was underpinned by varying views of the data and differing skillsets.

7.2.4 Revised Sources of Power

The central focus of this research was to establish the extent to which BI impacts power dynamics, through the lenses of various sources of organisational power. Accordingly, the Table below reflects the relevance of Meaning, Process or Resource from the context of this research:

Sources of Power	Demonstrated in Literature	Case study findings
Process power	✓	×
Resource power	✓	✓
Meaning power	✓	×

Table 7.4: Revised sources of organisational power

- ***Resource power***

This research revealed that the source of power which had the most influence within the organisation was 'resource power', specifically from the context of the expertise and knowledge of organisational actor. When exploring the extent to which BI impacted power dynamics, it was clear that having the ability to make decisions (Process power) was ineffective in managing and influencing power dynamics, this was reflected through how the functional managers, who had decision-making authority were unable to exert their influence on other actors, such as the analysts due to their limited know-how of BI. Furthermore, groups of actors did not seem to have the ability to manage interorganisational power either, this was seen through how there was in-fighting and much tension within the same group of actors, such as the

analysts for instance. Therefore, it was solely through having expertise and knowledge of both the analytical tool and the institutional knowledge which led to a shift in power dynamics, from the managers towards the in-house analysts, particularly during stages of BI articulation.

- ***Institutional knowledge***

The revised conceptual framework features 'Institutional knowledge' which was seen as playing a vital factor in the way BI technology was enacted by organisational actors, particularly between the central analysts and in-house analysts. It was also seen as playing a significant role in impacting power dynamics within the trust, namely through the in-house analysts. The important role of institutional knowledge is reflected in the framework through the different sized arrow and shading, signifying strength of influence.

7.3 Proposition testing and discussions

Proposition 1: *The role of BI impacts power dynamics between clinicians and Data analysts, whereby the data analysts are more influential.*

Therefore, in exploring Proposition 1 of this research, it is suggested that human behavioural factors were seen to influence the way in which BI is enacted and used by organisational actors. For instance, it is established that groups of organisational actors hold similar traits in accordance to their roles. An example of this was the central analysts, who were generally considered less forthcoming by colleagues and less willing to engage in discussions, as compared to the functional, operational actors. Therefore, given their strong analytical inclinations and reliance limited reliance on intuition, their enactment of BI was more objective and rooted in the data, as opposed to being enacted more collaboratively. There was explicit reference to their 'personalities' and 'introvert nature', which resulted in them using BI in a fairly isolated and remote manner. On the contrary, it is argued that the in-house analysts enacted the

technology differently to their central analyst counter-parts. Much of this was attributed to their continued interactions with operational staff, which is also reflected through their behavioural factors. For instance, the in-house analysts were also seen to pursuit their intuition and curiosity, despite being in a data-driven role, due to their presence in the wards and other operational settings. It was also seen that behavioural factors also impacted the way in which the functional managers utilised BI. Their enactment of BI was apparent through the combination of their high reliance on personal experiences, intuition pertaining to what occurs within the operational settings and their underlying desire of successfully submitting business cases to the senior board. All these factors were seen as being critical to the enactment of BI by functional managers.

Proposition 2*: Environmental factors influence the way in which BI is enacted and used by various organisational actors*

The findings also provided valuable insights into proposition 2, highlighting the role of environmental and contextual factors in impacting how BI is enacted by NHS organisational actors. The challenges the NHS face are well documented in empirical studies and further surfaced in this research. It was evident that time pressures and performance challenges were key factors which impacted the way in which BI was used amongst the organisational actors. This is in line with Orasanu & Connolly (1993) who posit that decisions which are made under difficult conditions, such as limited time, uncertainty, high stakes, vague goals, and unstable conditions are conducted in particular ways. More specifically and tying up with the earlier discussions relating to behavioural factors, it was evident that the central analysts, given the nature of their role and the target driven environments in which they operate, meant they enact the BI differently to others in the organisation. There was seen to use BI merely for reporting purposes, with little personalisation or contextual detail. Many of the central analysts made the point that due to them having to meet sporadic targets from across the trust, meant they had little time to deliberate and discuss BI data with the end users, such as the functional managers and

service managers. This criticism was also levelled towards the central analysts by the functional managers, who stated that often they would receive BI generated data and reports emanating from the central analysts, which either had little practical relevance or that limited explanations would be provided by the central analysts. After probing this, the central analysts revealed that ideally their interaction with functional managers and other requester of information should be iterative, whereby they pose further questions to fully understand and establish the purposes and proposed end-uses of the data, however given the amount of queries which they deal with on a daily basis, it becomes very difficult to provide such personalised, iterative insights, therefore highlighting the role of environmental factors in the way BI technology is enacted by the central analysts.

Exploring this further, it was also evident that due the in-house analysts were seen as being more reliable and integrated into the environment, which also reflected the way in which they would use the BI, as highlighted in more detail further on.

Proposition 3*: The way in which BI is enacted by organisational actors impacts BI articulation and the BI decision-making process*

This research also provided some relevant insights into proposition 3, which postulated that the way in which BI is enacted impacts BI articulation as well as the overall decision-making process. This was evident from both central and in-house analysts as well as the functional managers. It was established that the time and target driven environments in which the central analysts operated reflected on their priorities, ways of working and ultimately their utilisation of BI. Their articulation significantly differed from that of the in-house analysts, who enacted BI more flexibly and accommodatingly. Thus, the way in which BI was used would ultimately impact how the analyst and managers would interact with one another, as well as influencing the nature of these interactions. For instance, the central analysts used BI on a trust wide level, therefore their use of BI was solely for report building and responding to

queries on an ad-hoc basis, thus having a limited direct influence on the eventual decision resulting from the use of BI generated data. Similarly, from the context of the functional managers, due to diverging skill sets, it was evident that service managers who had an analytical background or some BI analytical skills, would enact differently to service managers with no analytical skills. The findings revealed that service managers who were relatively comfortable in their analytical ability would ask relevant and appropriate questions to the central analysts and therefore the articulation would be, though not always harmonious, but certainly relevant. Furthermore, in exploring the enactment of BI by functional managers, it was revealed that they would mainly use BI for the purposes of disproving myths validating personal opinion. Many of the functional managers highlighted their heavy reliance on their personal intuition and gut feeling, however the functional managers found the use of BI highly useful not necessarily for decision-making purposes, but rather to overcome misconceptions and myths within their services.

The transparent and flexible manner in which the in-house analyst enacted BI also impacted the articulation which occurred between them and the functional managers. In addition to utilising the analytical skills, the in-house analysts would also rely upon some of their domain expertise built up over time. Therefore, by enacting BI less rigid than the central analysts, more fruitful discussions and overall BI articulations would manifest between the in-house analysts and the functional managers. However, the findings also indicated that the functional managers would be highly reliant on the interpretation and analytical skills of the in-house analyst. Therefore, the functional managers were seen on occasions to appease the in-house analyst, particularly for the purposes of business cases, which typically required the inclusion of data driven justifications. Given the diverging use of BI by both the in-house analysts and the central analysts, it was clear that the in-house analyst had more influence during their articulation with other organisational actors and given the way in which they were able to use BI, whilst also remaining true to the context enabled them to have more significant impact on the decision-

making process than perhaps the central analysts. Ultimately it is evident that the way in which organisational actors enact BI has an impact on interactions between groups of actors as well as the impacting decision-making processes.

Proposition 4*: Data articulation occurs between various organsational actors during BI decision-making*

Interestingly, in exploring the data articulation between organisational actors during BI decision-making, it was evident that limited articulation and deliberation takes place between operational managers and the central analysts. As highlighted earlier, given that the central-analysts operate remotely from the wards and care groups meant that interactions between both remained limited, often merely done through several email exchanges. Conversely, and in-line with Shollo and Galliers (2016) it was evident that the in-house analysts were able to articulate their findings and interpretations of the BI generated data more frequently and openly with functional and operational managers. While this was largely due to them being positioned within the wards and clinical care groups, the fact that they were also well acquainted with the processes within their settings and thus, acquired the institutional knowledge, enabled them to see the data from more than one perspective. Therefore while the in-house analyst was able to use this in his/her advantage, it allowed form more transparent and regular articulations to occur between themselves and the functional managers. Therefore, the 'data articulation' which Shollo and Galliers (2016) report between analysts and managers is further explored in this research, by identifying the disparate nature of articulation which occurs between managers and either central analysts and in-house analysts.

Proposition 5*: The use and BI technology enactment by organisational actors within the NHS is bringing about a shift in power dynamics through 'Resource, Meaning and/or Process' power dimensions.*

In the exploration of proposition 5, this research acknowledges the role of BI in shifting power dynamics between organisational actors. However, the organisational source of power most prevalent as a result of BI use within the NHS was that of 'resource power', more so in relation to resource as expertise. It is evident from the discussions and the analysis conducted therein, that the in-house analysts through the analytical expertise and more importantly their institutional expertise enabled them to become more influential within their organisational settings. More specifically, it was evident that the central analysts, though technically were highly proficient, lacked the contextual knowledge, therefore leading to many of their reports and recommendations being inappropriate or not of much relevance. Specifically, from the context of power dynamics, it is argued that the functional managers who would request data and reports from the central analysts for decision-making would often resort to overlooking the data generated or going with their gut feeling, which signifies the dominating role of process power. Conversely, the in-house analysts ability to supplement data with the context made them highly valuable assets within a healthcare context. Furthermore, the reliance of functional managers on the in-house analysts also the signifies the influence of in-house analysts and how 'resource power' was able to supersede the 'process power', held and typically associated with managerial decision-making power. Accordingly, whilst existing studies have acknowledged the importance of domain knowledge, this research contributes further by emphasising the role of institutional knowledge in organisational power dynamics and how it can lead to actors having influence without authority, particularly in the case of the in-house analysts within this research.

Proposition 6: *Environmental and behaviour factors also has an indirect impact on power dynamics between various actors*

In the exploration of proposition six, it is highlighted that environmental factors also impact power dynamics within the organisation. This is evident when

comparing the factors which led to divergence of BI enactment between central and in-house analysts. The environmental factors were found to have a profound impact on the actors behavioural tendencies, which is played out between the various actors, thus also impacting power dynamics. The environment in which the central analysts operated influence the way they behaved and operated the BI technology. Given their time constraints and highly target driven roles, they would generate many reports and insights, which were considered less relevant and therefore often over looked by functional managers. Thus, their enactment of BI which was impacted by the environment they operated in indirectly impacted power dynamics between actors, such as them and the functional managers, as by merely overlooking the BI data, the functional managers would signify they were in control. Conversely, while Osman and Anouze (2014) argues that managerial subjectivity bias, and decisions made based on intuitive gut feeling can lead to an adverse impact on an organisation, it was evident that the in-house analysts, given their contextual proximity to the wards and care group operations would behave more intuitively and balance their objectivity with the contextual factors. Thus, in doing so they were considered a very valuable resource by both senior management and functional managers, leading to influence without authority. These propositions are discussed in further detail in line with the academic literature.

7.3.1 Conceptual frames of reference

Building on Shollo and Galliers (2016), this research explores what actually occurs during the BI decision-making process interplayed between managers and the analysts. While Shollo and Galliers (2016), extensively referred to the process of ‘articulation’ that manifests between managers and analysts, this research was able to differentiate between the types of ‘articulation’ that occurred between these divergent sets of organisational actors. Although there are similarities and agreement in the fact that BI generated data triggers discussions between various actors, the extent to which this occurs varies, depending on the context and more so, whom the articulation is taking place

between. As highlighted in this analysis, there were many contestations resulting from BI use between these actors, more frequently however between the functional managers and the central analysts, attributed to the fact that the analysts operated disparately, away from the context and thus were often unable to provide a true or accurate reflection of what occurred within the various services. In order to contextualise the findings, the Figure 7.2 depicts the critical role of institutional knowledge and how it plays a role in influencing organisational power dynamics, which is discussed in more detail later.

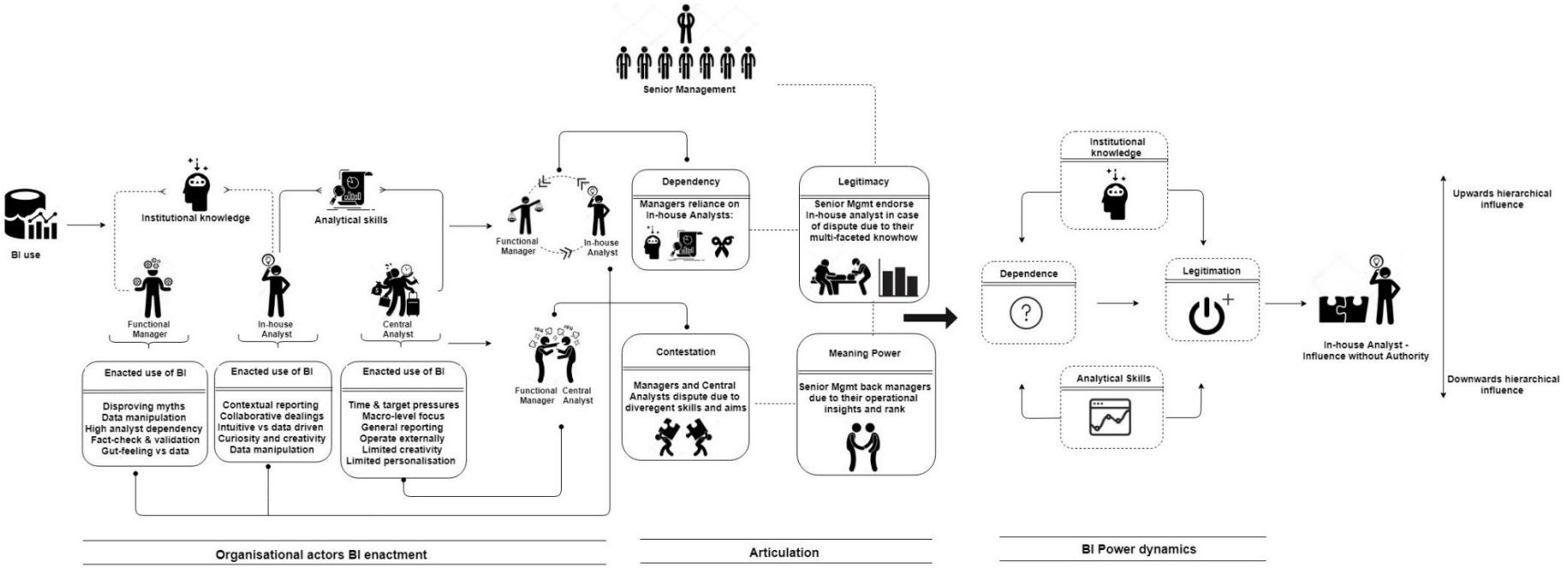


Figure 7.2: Conceptual depiction of Power dynamics

Foshay and Kuziemsky, (2014) investigate an implementation framework for BI within healthcare and posit that it is not solely IS skills which are required, rather it is also imperative that organisational actors, such as functional managers also possess data analysis skills. However, this segment of this BI Institutional knowledge framework (Figure 7.2) highlights that while the functional managers have institutional knowledge, represented through the contextual insights they are exposed to, they lack the more analytical skills, thus predominantly apply BI based on their experiences and contextual know-how. Conversely, it is seen that the central analysts benefit from having analytical skills, yet lack the institutional knowledge, due to their disposition, location and nature of their roles. More importantly, it is the in-house analyst who benefits from both paradigms, the institutional knowledge as well as the analytical skills. Consequently, this particular organisational actor is able to use BI, more flexibly, contextually and effectively as discussed further. Therefore, while the extant literature recognises the need for service managers to also be data savvy, the findings of this research suggest that equally, the data analysts should also be 'contextually savvy' and acquire institutional knowledge and know-how for effective use of BI.

7.3.2 Business Intelligence Technology Enactment

Furthermore, as emphasised in Figure 7.1, this research through the use of the Conceptual Framework, also provides pertinent insights into how BI is enacted by the various organisational actors and the role of contextual factors and the environment in influencing how this technology is enacted. For instance, it was revealed that due to time constraints, target and performance pressures, the central analysts would use the BI in a particular manner, which differed to other analysts, such as the in-house analysts. As such, these set of data analysts were more concerned with macro level, generic reporting and were fixated on completing their 'job tasks', with little if any, additional personalisation and creativity in the representation of their generated BI. While it was revealed that the central analysts would like to delve further and explore the ambiguities and curiosities resulting from the queries posed to them by

functional managers, the environment in which they operated made it virtually impossible for them to do so. This is also supported by studies which have previously indicated that the enactment process and contextual environment are interdependent upon one another (Reed 1997; Pawlowski & Robey, 2004). Resonating with this, Feldman (2004) also argues that enactment in its essence concerns the behaviour of managers impacted by societal norms, which is apparent in their responses and interactions to institutional events and structures. As such, this research also highlights this through the way in which the functional managers interact with the BI data, particularly when the BI generated data may oppose their natural disposition and inclinations. Moreover, the literature also reports that enactment is dependent upon contextual settings as organisational actors react to changing organisational requirements (Daneels, 2003; Chan et al., 2011). Similarly, it is argued that the use BI by the organisational actors within this case context is also influenced by contextual environment (Weick 1979; 2001), thus through this, actors invasively construct their environment (Rindova et al. 2004).

Fundamentally, one may argue that the role of the BI system is to enhance the timeliness and quality of data accessible for managerial decision-making, therefore suggesting that actionable information has to be supplied at the right time, in the right location and also in the right form (Negash 2004). Nonetheless, given the contextual challenges faced by the central analysts in this research, it was evident that they were often unable to provide information in a timely manner, nor in the most appropriate format. Accordingly, this would influence the way in which functional managers would operationalise this data, as seen by them commonly reverting to their hunches as a means to validate the data, as also discussed in more detail further. Similarly, given the relevance of the contextual surroundings, the in-house analysts were also found to shift from their highly analytical disposition and incorporate more ‘soft factors’ as a way of negotiating BI use within their environment. Therefore, the way in which the BI technology is enacted, is contingent upon the environment and context of its use, thus further supporting the notion that both the enactment process and the contextual environment are interrelated (Reed

1997). This coupling of enactment and environmental processes was further highlighted by central analysts, that previously held in-house analyst roles, whom admittedly highlighted the role of environmental stimuli on the way in which they used BI.

7.3.3 Business Intelligence articulation

Given that healthcare processes are not isolated events, the interactions between processes, people and the use of technology is a worthy point of discussion, however previous literature exploring BI use has largely overlooked human agency and more so ignored how BI is used and negotiated between various organisational actors. Acknowledging this is pertinent particularly from a power dynamics perspective, as gaining an understanding of how certain organisational actors may be able to coerce others into accepting their views within such interactions, reveals a lot about power consideration and the ability to influence. Therefore, through focusing on the enactment of BI by various organisational actors, the underlying role of context surfaced as being highly relevant when establishing how BI is negotiated. In extension of the discussions relating to 'articulation' highlighted by Shollo and Galliers (2016), this research reveals that articulation differs between the functional managers and central analysts and the functional managers and in-house analysts, with much of this as a result of how the BI is enacted by the actors in the first instance. It was evident that limited articulation occurred between functional managers and central analysts, nonetheless the findings reveal that although articulation between these actors are limited, when they did occur, it was conducted in a confrontational and inharmonious manner. This is depicted within the 'BI Institutional knowledge framework' whereby both set of actors are seen quarrelling due to their divergent focuses and skills. Much of this disparity can be explicated through an appreciation of the role of the intuition and analytics dichotomy, which is explored in more detail further in this section. Conversely, this conceptual framework also highlights that the in-house analyst and the functional managers share a more steady,

harmonious and frequent exchanges, thus revealing the varying nature of articulation occurring between organisational actors, which previously has not been acknowledged.

Shollo and Galliers (2016), posit that articulation consists of three main aspects, articulating new distinctions, whereby new distinctions emerge from BI data, articulating different perspectives, in which discussions commence between various stakeholders to discuss the new distinctions, and thirdly organisational actions, which indicate that some form of action is taken based on the discussions. Within the context of this research, it is evident that this does not occur much between functional management and the central analysts due to their disparate ways of working and limited contact. Foshay and Kuziemsky (2014) argue the need for appropriate processes to be in place which enables the effective dissemination of BI information between various organisational actors. Given the limited BI skills of the functional managers identified in this research, it is evident that such processes were loosely in place, particularly since the central analysts were geographically located away from the environment, therefore resulting in limited interactions between both sets of organisational actors. However, articulation between the in-house analysts and the functional management is more regular, through which the in-house analysts are able to influence the discussions through their ability of not only understanding the data and its implications, but also through their contextual insight and ability to supplement the analytical know-how with the institutional knowledge. As such, and in agreement with Shollo and Galliers (2016), it can be suggested that during the processes of articulation, tacit knowledge may be transferred from one organisational actors to the other, however the ability to successfully convey and influence the discussions largely depends on the ability to converge analytical and institutional knowledge by the organisational actor. This is supported further by Barki and Hartwick (1994) who posit that when users have influence, they generally get what they want and experience less conflict.

7.3.4 Contextual factors and Actor Dissonance

Therefore, the role of context and understanding the intricacies within the NHS is just as important as the analytical skills acquired for effective decision-making. This research also highlighted the fragmentation and the silo, disparate manner in which the trust largely operates, and this is reflected through the disconnected ways of working of organisational actors within the same group groups. A prime example of this was how the data analysts within this case context operated incongruently, lacking transparency and in pursuit of differing goals. Befittingly, through the concept of Co-agency, which refers to the synergy between humans, technology and processes within a service of the jointly held goals (Thraen et al., 2012), it is argued that healthcare processes are not isolated events, therefore the interactions between processes, people and the use of technology should be acknowledged, with the aim of reducing opaqueness between them (Foshay and Kuziemsky, 2014). Accordingly, within the context of managerial healthcare processes, i.e., decision-making, much of this opacity is as a result of divergent skills and differing perspectives, which, as highlighted by the BI Institutional Knowledge framework, can be reduced through supplementing analytics skill-sets with institutional knowledge.

Much of the dissonance and contestations highlighted within this research is attributed to organisational actors failing to understand more in relation to each other's domain. Thraen (et al., 2012) refers to this as contextual dissonance, which is prevalent within the healthcare sector. The authors argue that coordinating operations across the continuum of care is challenging given the need to understand functions in differing contextual environments. This is exasperated by the fact that clinical contexts may differ in terms of their goals, the managerial actors may also pursue divergent goals, whilst the senior management from a macro level may be imposing a completely different direction. Accordingly, this research has contributed to this discussion by highlighting that while BI systems can provide transparency and offer a pervasive layer of intelligence to the organisations, which can reduce the gap

between the various services within the NHS, it is important to acknowledge the role of the in-house data analyst in minimising the contextual dissonance plagued within the NHS trusts.

While it is acknowledged that finding common ground across the health care sector as a whole is challenge, establishing a common ground within each trust is also a challenge as highlighted in the analysis. Previous research has highlighted the centrality of contextual factors, in achieving effective performance management systems (Ferreira and Otley, 2009), however, this research extends this by emphasising the pivotal role of context in managing power dynamics. Therefore, from within a BI decision-making context, it is the in-house data analyst who to is able to bridge the management-analyst dichotomy. Furthermore, it is also due to this ability of the in-house analyst that he/she is able to achieve legitimation from the senior management, thus leading to a shift in power dynamics and increasing their influence within the organisation.

Although it has been acknowledged that BI contestations occur between the various actors during the stages of articulation, the fundamental reasons as to why this occurs, and how it impacts power dynamics requires further discussion. From a clinical point of view, it is argued that the use of BI not only enhances the outcomes of healthcare organisations, (Tremblay et al., 2012, Pine et al., 2012), but can also play a pivotal role in progressing from intuitive to precision medicine (Christensen et al., 2009, Gastaldi et al., 2015). Similarly, from a managerial perspective, it is assumed that the use of BI can assist in moving from intuitive to more data-driven decision-making (ADD WIXOM), nonetheless, as the findings indicate, the operational managers are still heavily reliant on their personal intuition and gut feeling when making decisions, regardless of their access to BI generated outputs such as reports and dashboards. Accordingly, this research also contributes further to healthcare literature through the findings which highlighted the dichotomy of intuitive and analytical approaches to decision-making.

7.3.5 Healthcare and intuitive decision-making

While these components of decision-making have widely attracted academic attention, within healthcare literature it has been explored largely from within a nursing context (Lamond & Thompson, 2000; Thompson & Yang, 2009). Accordingly, this research contributes further to these discussions discussion by exploring this dyad from a management decision-making context within the healthcare. The subjectivity and bias of management is widely reported (Banker et al. 2004; Kaplan 2012). Accordingly, a key discussion that commonly resurfaced when exploring the use of BI by the functional managers and analysts was that of their reliance on 'gut feeling' and personal 'hunches'. An extensive discussion into this is evident in section 6.3, which, through the guide of the conceptual framework, revealed how the functional managers use BI generated data as a means to fact check against their intuition and perceptions. More importantly, it was revealed that the functional managers would occasionally overlook the data in pursuit of evidencing their personal intuition and gut-feeling. Although other organisational actors, including the central analysts would acknowledge the importance of their intuition and gut feelings, the operationalisation of decisions based on 'gut feelings' by the functional managers was received more cautiously, given the implications and possible impact of their decisions.

According to Standing (2010), intuitive decision making is mainly descriptive, and its applicability has been viewed from within a context of human judgement. The role of context has been a central finding of this research, accordingly, the relevance of context and its pertinent role in decision-making has also been acknowledged in the extant literature from within the healthcare context. Interestingly from a clinical perspective, it is argued that the social contexts can considerably influence the types of decision made on the ground (Parker-Tomlin et al. 2017). The social context may require a modification in clinical skills in response to environmental and social variations to inform decisions, particularly in situations where client interactions necessitate prompt responses (Welsh & Lyons, 2001). Accordingly, intuitive decision making is evident within healthcare contexts, particularly client centred environments and reflective practice, and ultimately seen as maximising

complex clinical decision-making processes to provide a better service to patients (Nyatanga & Vocht, 2008). As such, this research also reveals that service managers may heavily rely on their personal intuition as a result of contextual changes which they are aware of, due to their close proximity of being within the client centred environment, as opposed to the central analysts who are predominantly uninformed of the social context, thus, unable to provide appropriate analysis. More so, it can also be argued that due to the in-house analysts being in regular contact with both functional managers and clinicians, within the clinical, patient focused environments, explains their reluctance in completely dismissing the intuition of their colleagues, which may even oppose their own analyses.

As such, Standing (2010) posits that such intuitive approaches can be extolled for considering the dynamic intricacies of human interaction and for its recognition of the influence of social contexts and real-life situations on such outcomes as judgements and decisions. Nonetheless, this approach is scrutinised due to judgements and processing information being prone to cognitive biases (Ibid), which consequently were also the criticisms levelled at the functional managers by the central analysts in this research. Furthermore, it is argued that this reliance on subjective gut feelings is often underpinned by a short-term focus, overlooking more long-term measures of risks implications. Therefore, the implications of solely relying on hunches can be highly detrimental (Anderson & Kilduff, 2009, Guerra-López & Toker, 2012). Moreover, interprofessional healthcare research concerning divergent actors has typically concentrated on the strengths of analytical approaches and the weakness of intuitive approaches to decision-making processes (Cabantous & Gond, 2011; Gilovich et al., 2002). However, such decision-making biases have also been observed previously. Earlier literature has acknowledged and focused on decision-making approaches in ‘real-world settings’ (Klien 2008), thus highlighting decisions which are made under difficult conditions, such as limited time, uncertainty, high stakes, vague goals, and unstable conditions (Orasanu & Connolly, 1993) are conducted in particular ways.

For instance, the Cognitive Continuum Theory (Hannond et al., 1987), argues that decisions differ in the extent to which they rely on intuitive and analytical processes. As such, circumstances such as the availability of information and time fundamentally determines where a decision fits on this continuum, and whether organisational actors rely more on patterns or on functional relationships. Thus, relating back to the findings from this research, it was evident that the service managers were seen to heavily rely on their personal 'gut-feelings' and 'hunches', in spite of having data which may oppose their immediate inclinations. This can be explained through the application of Hannond et al. (1987) Cognitive Continuum Theory in that, the service managers lack time, give the dynamic and target driven nature of their roles and were also found to disagree with the analysis provided by central analysts, due to it often lacking applicability to their contexts. Accordingly, a pertinent factor which explains their behaviour and the continued reliance upon their intuition can be explained by the limited availability of time, incompleteness of information and also the nature of their fire-fighting tasks and activities, which can be categorised as the 'poor task structures' (Hannond et al., 1987) which they inherit as part of their operational role.

Conversely, given that the in-house analysts were able to foster more fruitful contact with these functional managers can be attributed to the fact that, often the tasks are more structured and not on an ad-hoc basis, due to the analysts being an internal resource, and that the analysts are able to provide more meaningful, contextual information. Thus, these facts assist in bringing about a decision-making equilibrium which consists of both intuitive and analytical processes, for both the functional managers and the in-house analysts. Therefore, task conditions surrounding the environment and BI application are vital indicators of the extent to which managers may exercise intuition or analytical processes in their decision-making.

Supporting this further, Bonabeau (2003) present empirical evidence which indicates that more than 50% of corporate executives engage in intuitive "gut-feeling" decisions when challenged with multi-dimension complex alternatives. As there is no guarantee that this is the best course of action, such

methodology can have an adverse impact. Maisel et al., (2013) attribute such use of intuition to ‘confirmation bias’, whereby managers are able to convince themselves and on occasions, others, that their intuition and gut feelings are acceptable masquerades for having factual information. It was evident in this research that the managers would engage with BI generated data in order to either disprove myths, or as a means to disprove the data itself, or merely for validation purposes. This resonates with Maisel et al., (2013) who argue that managers often resort to confirmation bias in pursuit of achieving a desired outcome. The authors further argue that managers do not start by framing a problem before collecting or requesting information that will lead to their conclusions, rather they subconsciously start with a preconception, therefore they only pursue data that will endorse their biases. Thus, the adverse impact is that managers may prepare themselves for a situation, when in reality, a completely different situation which is occurring. However, it can also be argued that this reliance on ‘gut feeling’ is magnified and exaggerated as a result of the highly antithetical offering of the central analysts, who due to their lack of contextual insights and institutional know-how would often present findings that would be in stark opposition to that of the managers. Therefore, pushing managers even further along their intuitive disposition.

Therefore, it is argued that through framing a problem and taking into consideration alternative points of view, may enable managers to broaden their options to formulate hypotheses, which is where BI and other forms of analytics would take its place. Accordingly, new analytical tools can be used to enhance organisational actors decision-making through exploring a variety of options and supplementing human judgment and the intuition of experienced actors with integrating decision sciences, agent based modelling, artificial and interactive optimization evolution processes to leverage their managerial instinct without limiting themselves by its weaknesses. Although, (Osman and Anouze 2014) refers to the situation through a managerial context, it is evident from the findings of this research that, in fact, it is the in-house analyst, who is able to leverage the managerial instinct, while not being in a managerial position, through their analytical skills and through their ability

of exercising human judgement which is informed through the accumulated intuition of their peers. As such, making the in-house analyst a valued resource.

Nonetheless, the severity of solely relying on gut-feeling is widely reported in the extant literature as is attributed to hindering performance growth. Osman and Anouze (2014) argues that management subjectivity bias, and decisions made based on intuitive gut feeling can lead to an adverse impact on an organisation. Nonetheless, the findings also indicate that functional managers are unable to commit decisions entirely based on their gut feelings, given the information culture and data driven decision-making focus of the organisation as a whole. Thus, acknowledging the perils associated with intuitive decision-making, may further explain the organisational legitimacy that the in-house analysts are able to attain from the senior board of directors. The findings revealed that, when the in-house analysts and the functional managers were unable to reach an agreement, managers of high seniority would demonstrate a willingness to support and back the in-house analysts. Therefore, in doing so it is argued that the senior management felt they were able to offset the intuitiveness of the managers with more fact-based information provided by the in-house analyst, particularly given that the latter is also a recipient of the intuition on the ground. Similar findings are present from a study conducted by Spehar et al. (2014), in which it was identified from a clinical context that by not having a medical background, nurses felt their impact upwards in the organisation was limited, thus they resorted to relying on 'disguising' themselves as doctors. Resonating with this, the findings from this research also emphasis the role of having a professional background as means of gaining acceptance and support from higher up in the hierarchy. However, in contrast to Spehar et al. (2014), the 'professional background' in this research consisted of the contextual background and analytical skills, rather than a medical background. Therefore, through the legitimation and endorsement, the in-house analysts are able to receive from the senior executive board of directors, emphasises the role of non-decision making and the fact that, the

most visible decision makers, i.e. the functional managers in this research, are not necessarily the most powerful (Hardy, 1996).

More importantly, the ability of the in-house analyst to balance the intuitiveness and subjectivity of the functional managers with the objectivity from the BI data played a major role in their ability to influence decisions and become more dominant actors within their environment. However, it is pertinent to mention that while in-house analyst are becoming more dominant within their disposition, they are able to achieve this through harmony and cohesion, factors often overlooked in the extant literature when discussing the dominance of organisational actors over others. The term *dominance* implies behaviours which entail bullying, intimidation, with previous studies also supporting this notion whereby organisational influence is seen to be achieved through draconian tactics (Lee & Ofshe, 1981; Mazur, 1985). Yet on the contrary, this research highlights that dominance and influence can be achieved without having to resort to heavy-handedness. Therefore, the findings from this research resonate with Anderson and Kilduf (2009), who argue that influence can also be attained through display of competency and by indicating one's value to a given group. Which is highlighted by the in-house analysts, whom through their multifaceted skills can attain dominance to some extent by receiving support from their 'manager's, manager' and other senior managers, whilst also highlighting their worth to the functional managers. As such and in contrast to previous studies, this research posits that dominant organisational actors are able to attain influence through displaying self-confidence and competence as opposed to behaving in an oppression and threatening manner. Thus, by the same token, also in agreement with previous studies which highlight organisational actors who ploy aggression and unmannerly behaviour may not necessarily achieve influence, as also reflect by the contestations which occur between the central analysts and functional managers (Ridgeway, 1987; Ridgeway & Diekema, 1989; Van Vugt, 2006).

7.3.6 Dominant organisational actors

Moreover, findings from the study conducted by Anderson and Kilduf (2009), also revealed that dominant organisational actors may also ascend group hierarchies through the ability of appearing helpful to a particular groups aspirations and overall success, as opposed to portraying oneself as aggressively attempting to seize power. This research also concurs with this, in that in-house analysts who lacks seniority, are able to gain the support of some of the senior and most powerful decision-makers within the trust, in the process having more influence than their functional managers, primarily due to their strong analytical skills and the endorsement of data driven decisions, which senior board of directors are driving both as a strategic vision and as part of the organisation's wider digitisation roadmap. Here, in line with Anderson and Kilduf (2009), it can be argued that the in-house analysts are considered as highly valuable resources, of 'little risk' by the senior management. Therefore, through contributing towards and supporting the wider organisational culture and drive on data driven decision-making, the in-house analysts are seen to achieve 'influence without authority' (Johnson 2008), as such highlighting the ability to shift power dynamics through the use of BI.

It has previously been acknowledged that organisational actors able to attain dominance is not necessarily due to general cognitive ability but may also be as a result of social skills such as extent to which one is able to manage conflict and interpret the emotions of others (Hall, Halberstadt, & O'Brien, 1997). In the context of this research, the findings suggested that various organisational actors held particular personalities traits. While much of the discussions related to the general personality and characteristics of certain actors within a particular group, these insights resonate with Orlikwoski and Gash (1992) who argue that in relation to Information Technology use within organizations, typically a number of critical social groups-in referred as the 'social world of computing' (Kling and Gerson 1978) whose actions certainly impact the process and outcome of technological change. Accordingly, organisational actors such as functional Managers, system developers, and users, can be

considered the key actors, and by dint of their membership in particular social groups and the different roles and relationships. It was emphasised by some of the functional managers that the central analysts were rather introvert in nature, more ‘geeky’ and preferred to work through their tasks with little if any interaction with others. Therefore, in comparison to the in-house analysts, it is argued that the central analysts due to the inability and potentially limited display of social interactions are unable in this regard to assert dominance and influence within the organisation. Therefore, given that the functional managers and the central analysts generally lacked communication and shared limited interactions, may also indicate their inability of influencing the functional managers away from their intuitive disposition, as also reflected in the analysis section. Alternatively, the dominance and influential disposition of the in-house analysts may also be contributed to the fact that individuals who have high trait dominance are able to make more suggestions and expressed opinions more frequently (Kalma, Visser, & Peeters, 1993; Moskowitz, 1990), converse in more firm tones (Aries et al., 1983; Buss, 1981) and make more direct eye contact (Snyder & Sutker, 1977). Accordingly, Johnson (2008) argues that the ability of organisational actors to constructively persuade and negotiate, the aim of attaining mutual benefit can vastly enhance one’s influenced the organisation. The findings highlight how the in-house analysts were able to take control of discussions during their articulation with functional managers due to their expertise and ability to make the functional managers either look ‘bad or very good’ through their representation of the data. Additionally, having the ability to express themselves, speak in an assertive manner and also make direct eye contact requires the analysts to be present, in in-person with the functional managers.

Consequently, the central analysts are located externally and operate away the environment and the findings also revealed that they would very rarely meet any of the functional managers in person. Conversely, the in-house analysts are embedded in the environment, thus also implying how being face-to-face in a group may facilitate the dominance of organisational actors. Supporting this, a plethora of studies have highlighted that individuals with

particular characteristics are able to attain more influence in face-to-face groups than others— as they speak more, acquire more control over group processes, and have more disproportionate sway over group decisions (Judge et al., 2002), such as decisions that occur within a ward or particular service within the trust. Additionally, the literature also emphasises the role of superficial cues, whereby organisational actors may be perceived to be more skilled through the use of more certain and factual language (Driskell, Olmstead, & Salas, 1993; Ridgeway, 1987), as well as being able to articulate in an assertive manner. Leading on from this, Anderson and Kilduff, (2009) argue that dominant organisational actors within a group setting are those who are able to exhibit competence-related cues, regardless of their actual ability, and it is such cues which notifies the perceptions of other members of the group, those eventually leading to higher dominance and influence. Similarly, it can be argued that by being in the environment, the in-house analysts are able to assert themselves, through their analytical and institutional insights, regardless of how informed they may be of every contextual details, which further highlights the importance of resource power and the role of face to face groups, in BI related power dynamics.

Orlikwoski and Gash (1991) argue that where the technological frames of key groups in organisations, such as managers, technologists, and users—are significantly dissimilar, complications and conflict surrounding the development, application, and change of the technology may result. This is evident within this research also, whereby, divergent organisational actors, such as functional managers and data analysts possess different technological frames, thus apply and enact the technology is different ways, to the extent that even the data analysts between themselves, utilise the BI technology differently. However, the fundamental role of the technology and context dyad has previously been acknowledged. For instance, Orlikwoski (1993) refers to technology frames, which is used to describe the understanding held between various organisational actors within a social group regarding certain technological artefacts. Importantly, she emphasises

the fact that these frames not only include knowledge regarding particular technology, but also the local understanding of its specific application within a given setting. Orlikwoski (1993) also acknowledges such contextual dimension of technology frames, as being significant, with the understanding of a technology as something which “can only be described and its significance appreciated in the context of its uses and its users” (Bloomberg 1986:42). In context of this research it can be argued that although the functional managers and in-house analysts, belong to divergent social groups, they share similar technology frames, particularly given the localised understanding and application of the BI technology by the embedded analysts.

This provides an opposing view to earlier literature, such as Calder and Schurr (1981) for instance, who posit group frames are less likely to be shared across dissimilar stakeholder groups. Accordingly, it can be argued that the ability of the in-house analysts to share technology frames with organisational actors with more of an operational disposition, enables the analyst to further enhance their institutional knowledge and local knowledge, whilst also ensuring the functional managers do not operate entirely on their hunches. Additionally, this crossover also benefits the in-house analysts, as this crossover and sharing of technology frames with operational staff assists in ensuring that the in-house analyst does not operate entirely from an objective disposition.

The importance of this institutional knowledge is evident from Figure 7.2, and has also been acknowledged previously. For instance, studies have explored Institutional dimensions, as such North (1990) refers to it as a complex phenomenon made up of legislation and regulations, cognitive factors, including culture and business practice (North, 1990) as well as social structures and social institutions (Fligstein, 1996). As such, the institutional context refers to the constraints devised by people that shape human interaction. Chetty et al. (2006) posit that continuous business experience increases the perceived importance of institutional knowledge within its context, as the increased experience within an ongoing business environment, assists in embedding one further in the local network. Therefore, having the ability to ascribe a specialism to a given context, its norms, rules, ways of

working is highly rewarding, accordingly, the real organisational value is being able to connect institutional knowledge to the right data (Goldman 2017). In recognising the importance of local knowledge and the need to understand micro-level sociology, Weick (1990:17) states that ‘cognition and micro-level processes are keys to understanding the organizational impact of new technologies’. In context of this research, it was revealed that this interplay between expertise and context, and having the understanding of practice from within the services and wards of the NHS Trust was critical for the successful use of BI. This was further exasperated by the fact that, while it is recognised that much of what is strategized within the NHS is driven by a top-down approach (Savage and Scott 2004), it is apparent that from within the local contexts, clinicians and functional managers tend to operate from a bottom-up approach whereby they are determinedly embedded in the clinical domain, and thus set improvement targets in-line with their knowledge of the local environment. This further explains how the central analysts, who are regarded as a corporate resource, as also highlighted in the findings, often have a macrolevel focus which is nor relevant, nor appropriate within the local context. It is here where the in-house analyst are able to differentiate themselves, through providing a more applicable and contextually relevant service.

7.3.7 Shift in power dynamics

The shift of power and influence in favour of the in-house analyst is resultant of the analysts, directly or indirectly acquiring multifaceted skills, through their manifestation within the actual services and wards itself. The key skills were identified as firstly, the technical, analytical skills where the analysts have the ability to and competently create codes upon request and also help identify particular trends within the wards. Additionally, the background knowledge that they acquired due to their presence in the wards, was a critical factor in their ability to influence the key workings within their environments. Therefore, they had the ability to articulate and present clear data narratives to the functional managers. Nonetheless, it was also identified that although there were disparities between the functional managers and the analysts, the analysts

themselves would differ extensively, and be critical of each other's skillsets. Supporting this, Howard et al. (2015), refers to the 'loose' infrastructure in place to develop information analysts within the NHS. He argues that given the evolving nature of technology and increasing requirements of managers and clinicians as a result of this data driven push, data analysts require development and investment if they are to embrace the digitisation challenges.

The findings also revealed that many of the functional managers were not confident in the ability of the analysts in fulfilling their data needs. This was more so the case for the central analysts. It was highlighted from both set of actors that often the BI generated reports either had little practical use or were completely irrelevant. This again resonates with Howard et al. (2015) who argues for the urgency in transitioning away from merely extracting data, to presenting a clear data narrative within the NHS, in order for managers and clinicians to make effective decisions. The findings further revealed many functional managers were of the view that, given the abundance of data being collected by the NHS, not enough was being done with the data. Such sentiments were underpinned by the fact that the BI systems were not doing enough to help prevent issues from occurring, but rather were being utilised for merely reporting purposes. Given that BI systems commonly rely on historic data to perform analysis (Dooley et al., 2017), it is evident that functional managers were referring to predictive analytics, or more timely forms of analysis, which would allow for a more proactive as opposed to reactive responses as a result of the generated data. Nevertheless, transitioning from historic analysis to predictive and even prescriptive forms of data analytics, requires proficient analytical skills, which as highlighted earlier, is an ongoing challenge within the NHS. A plethora of studies have identified the lack of skills and knowledge required for effective operational of decision-support information, therefore highlighting a pressing need for organisations to develop the appropriate IS skills and knowledge of its organisational actors in order to progress and effectively use BI tools (Ramamurthyet al. 2008; Popovic et al. 2012).

A critical success factor of BI identified within the literature is also the ability of providing convenient access to high quality information for decision-makers (Yeoh & Koronios, 2010). Therefore, in the context of this research, it is evident that the in-house analysts are able to fulfil this critical success factor through the ability of providing relevant, high-quality information, as opposed to information that may be considered of mediocrity quality due to a lack of contextual relevance. Thus, it is argued that in order for BI implementation within organisations to be a success, having in-house analysts, or analysts who were able to understand local dynamics is essential. Conversely, previous studies have too highlighted contextual factors as being less important. For instance, Dooley et al. (2017) highlighted that from a critical value factors in BI systems implementation, that contextual information quality was not regarded as a critical value factor of perceived information quality of BI implementation. The authors attribute this to the fact that BI inherently is rooted in historic data, thus provide a picture of what has 'occurred' as opposed to 'what is going to occur'. Therefore, given the response time expectations, the contextual aspects of information such as its timeliness, sufficiency, and relevance may be considered less important for BI systems, in comparison to live systems, which are more time dependent and transaction oriented.

The organisational culture of the NHS and it's top-down agendas are extensively discussed both in academic literature and also in the media, with such agendas often being attributed to tensions within the organisation. The inherently data driven culture of the NHS was extensively referred to by the participants of this research. Much of the sentiments centred on the fact that there was an expectation, regardless of skills and ability, to incorporate data driven decision-making at all levels of the organisation. It is anticipated that through enabling the "better use of information […] [that] will drive more effective and efficient services" within the NHS (Department of Health, 2012: 9) nonetheless, without excellent analytical skills becoming routinely available to all healthcare, this untapped power of healthcare information will remain unexploited. It is argued that the data driven focus of the NHS is a means to further fuel the organisations obsession in managing performance targets, as

reflected also by the tensions arising within clinician settings as a result of externally imposed performance targets which NHS trusts are expected to meet (Savage and Scott 2004). Gould (2003) argues ‘Some goals are implausible and unrealistic targets are being set. Even though we are improving performance, we are never going to hit these targets. We have to discard those things that don't work’, thus further highlighting the motives and underlying motivation for an increasingly data driven environment.

The findings also suggested that regardless of how the BI systems are being enacted within the NHS trust, it currently has little impact, thus resulting in little if any notable changes to services, with detailed discussions alluding to the lack of BI impact in section 6.4.3. While there are many contributory factors for this, it is argued that the organisational culture and recent digitisation commitments also play a major role in this. Providing a further perspective on this, Bowles (1991) argues that organisations have "shadows" which continually threaten to reveal themselves, and some organizations, alongside their principal actors, are constantly scrutinised, watched, and vigorously monitored (Sutton and Galuic, 1996). Accordingly, such perspectives are also for the NHS, whereby due to the organisations obsession with collecting data, its information-driven culture and organisations highly publicised commitment to operate paperless by 2020, are major sources of pressure, which impact the way in which organisational actors are expected to operate. Therefore, expanding on this point, it can be argued that if there was not such a data driven culture populated within the NHS, then some of the functional managers may not feel compelled to rely so instinctively on some of the in-house analysts, which as highlighted has led to a shift in power dynamics and organisational influence within the organisation. Supporting this further, it is also understood that an individuals’ influence is partially determined by the fit between their personality traits and their organization’s culture (Anderson, et al., 2008), therefore indicating that extent to which organisational actors are influential differs in different organizations. For instance, if the NHS was not heavily involved in digitisation and did not foster a data-driven culture, the extent to which the in-house analysts would gain senior management

legitimacy would not be as certain, nor would the functional managers need to count on the in-house analysts for ‘favours’ due to their dependency of their skills.

However, in support of the views of Anderson et al. (2008), the data obsessive culture of the NHS plays a major role in the organisational legitimacy some of the analysts received from the senior executive board of directors. Therefore, overall it is suggested that the organisational culture also plays a key role in impacting power dynamics in favour of the in-house analysts, whereby it was found that senior management were able to use the in-house analysts as agents to achieve strategic advantage, particularly given that studies have highlighted that policy makers struggle to understand the professional social structures which are prevalent within the local context, thus may hinder the effectiveness of policy drives (Currie et al., 2010; Martin and Waring 2013). Therefore, given the policy drives towards digitisation and the organisations commitment towards operating as a paperless organisation, may further explain the senior management acceptability of the in-house analysts, who are embedded within the local environments. Such top-down policy drives were event during various meetings, whereby functional management would feel compelled to provide insights into data and present some form of analysis, as this manifested as the ‘norm’ expectation across the trust. This resonates with Milne et al. (2002), who outlines that often managers may present various accounts to present a particular picture, whereas in reality such activities may simply be an elaborate and convincing frontage orchestrated or adopted to cover the "back stage" activities from prying eyes (Jackall, 1988: 162-90; Punch, 1996: 213-47). Milne et al., (2002), argues that such initiatives provide little if any change to ‘the real work’ of the organisation, as also highlighted within this case context.

Pfeffer (1973) uses the terms power and influence synonymously, as ultimately, it is through power that influence is gained. While Pfeffer and Salancik (1978) employed the concept of power to explain dependency, they explore this from an intra-organisational perspective, referring to external

resources. However, similarly one can argue that resource dependence can also be viewed from an intra-organisational perspective in reference to the reliance of expertise of particular organisational actors by others within the organisation. The BI Institutional Knowledge Framework reflects how the dependence of functional managers on the in-house analysts, further enhances the power and influence of the latter. Although the exact means through which dominant organisational actors achieve social influence has attracted varying views to date. This research presents profound insights into how social influence can be attained by organisational actors such as in-house analysts whom, according to their position within the hierarchy, may not readily be considered as being that dominant. It was evident that the analysts are a sought for resource particularly given their ability to represent the data in creative ways which reflected positively for managers. As such, the theme of 'Data manipulation' was extensively discussed by various participants of this research. This relates back to the earlier discussions regarding managerial gut-feeling and how their subjective disposition, heavily manifests in their personal intelligence, power and competence, rather than the realities (Osman and Anouze 2014). As such, they may require analysts to manipulate data that either conforms to their instinct or which will look more advantageous to senior members of the management board.

Accordingly, although Knights et al. (1993) explores interorganizational relations through political lens and posit that an advantage of collaboration is the potential of acquiring power and influence, it can be argued that intra-organisational collaboration can also be viewed through similar lenses. Predominantly when the collaborating actors may have differing goals, values and beliefs (Waddock, 1989), thus when the dispersal of power between the actors is unmatched (Gray and Hay, 1986), collaboration can be considered a means to protect specific organisational interests. The findings of this research reveal that while the in-house analyst are less influential than the functional manager, both in terms of authority and hierarchy, their capability of manipulating data to sensationalise results for functional managers, which is invaluable in a data-driven culture like the NHS, causes a shift of influence as

a result of the dependency and reliance of the functional managers on the in-house analyst. Therefore, this collaboration, potentially underpinned by reluctance and dependence can result in making the in-house analysts more influential in their disposition. This can be referred to as dependency collaboration, in that the functional managers are dependent on their analysts, not only for day to day, conventional querying, but also in order to sensationalise data to better reflect performance Figures and data within their service.

Previous studies have acknowledged the role of dependence power as stemming from the social expectation that those who are dependent on others, should receive the support and help required (Batson and Powell 2003; Berkowitz, 1972). Consequently, it is argued that legitimate dependency power is at play when organisational actors are aware of such dependency between themselves, whereby the dominant actors make it known that their ability of offering something requires the compliance of others (Elias, 2008). Accordingly, such intra-organisational collaborations within services and care groups can considerably disrupt power dynamics and shift influence as a result of resource power, i.e, expertise, in favour of the in-house analyst. Furthermore, while the in-house analyst is able to leverage resource power as a means to acquire some influence and dominance within their environment, the findings revealed that this organisational actor also has the ability to leverage influence beyond the functional manager, as emphasised in Figure 7.2 through the legitimacy and buy-in from senior management.

7.3.8 Co-optation of managerial culture

Accordingly, the Numerato et al. (2012), conducted a thorough review in which they state that the dynamics and interplay between managers and professionals may lead to five potential outcomes, such as (1) managerial hegemony; (2) co-optation; (3) negotiation; (4) strategic adaptation; and (5) professional resistance. While their study focuses on the interaction between

management and professionalism in relation to medical professionalism, this study can explore these outcomes as the consequence of interactions between management and the analytical profession. Accordingly, it was recognised that the interplay between functional managers and in-house analysts leads to both the co-optation and negotiation outcomes. Numerato et al. (2012) argue that managerial rhetoric does not necessarily have to be all-encompassing, thus professionals can exercise local control over their activities through the ability of utilising managerial principles, discourses and logic. As such, the interplay between functional managers and the in-house analysts enable the co-optation of managerial logic by the in-house analysts. As such, this allows the in-house analysts to exert influence downwards in the organisational hierarchy, towards clinicians due to their analytical skills and local knowledge which enables them to challenge the performance, and other metrics which the clinicians are required to abide by. It was often seen that; the central analysts would regularly flag up underperforming clinicians due to them not meeting targets or for taking longer for certain procedures. However, due to them not being in the local context, the findings revealed that often the central analysts would miss key contextual details, such as travel time between various parts of the ward, or pre and post procedure debriefs, which would reflect more negatively on the clinician performances. Resonating with this, Doolin (2004) explores the power and resistance in the implementation of a medical management information system within a healthcare context. Findings reveal how the implementation of the system was unable to facilitate a calculative form of control through computer-based surveillance and monitoring of doctors, as many of the doctors were able to resist the information generated through the systems by challenging its validity. Therefore, in this instance the clinicians were not passive subjects of a computerized control system. On the contrary, such issues were overcome in this research, in that the in-house analysts were able to supplement their analytical knowledge with the local environment, which meant they were acquainted with the procedures, local practices and daily routines and therefore were able to object to any challenges posed and counterchallenge the clinical staff. Therefore, making them more influential within the

environment, which as a result of co-opation of managerial culture, enabled downwards organisational influence.

Additionally, this BI interplay between functional managers and in-house analysts also led to negotiation, in that the functional managers would often find themselves negotiating with the in-house analyst as highlighted earlier, thus diminishing their own influence, thus allowing the in-house analyst to guarantee themselves authority and legitimacy through their ability of relating to the local context, and acknowledging managerial discourse whilst also having the ability to understand the analytical context. Therefore, through this ability and the dependency, the in-house analysts manage to exert influence upwards towards senior management. On the other hand, the BI interplay between functional management and the central analysts leads to professional opposition, which according to Numerato et al. (2012) in essence relates to management resistance and confrontation which has been discussed in detail the earlier sections.

7.4 BI Power Matrix

In summary of the key findings, this research also presents another key theoretical contribution in the form of the BI power matrix (Fig. 7.3), which in addition to the BI Institutional Knowledge Framework, also assists in evaluating the impact of BI use on power considerations. Accordingly, the BI Power Matrix addresses the relationship between BI use and power dynamics by exploring the key constructs identified in the research. As such, this matrix is a representation of the key findings from this research, in which the key organisational actors are mapped according to the degree of influence they are able to exert within the organisation as a result of their associated with BI (Figure 7.3). This matrix offers a four-way perspective of establishing the influence of an organisational actors, namely through the degree of institutional knowledge they possess, their analytical skills, the degree to which they are able to attain legitimation from senior management, and how the degree of dependence of others within the organisation are on them. As also

emphasised earlier, the in-house analyst, through their analytical and contextual know-how are able to secure senior management legitimation and support, thus making them highly influential in the organisation. Additionally, these skillsets also facilitate in the co-optation of managerial culture which enables the in-house analysts to hold clinicians accountable more effectively than the functional managers.

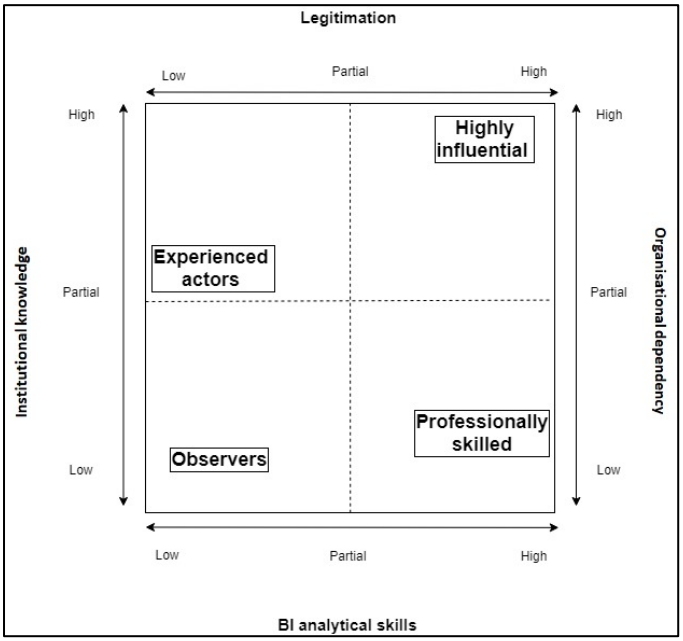


Figure 7.3: BI Power Matrix

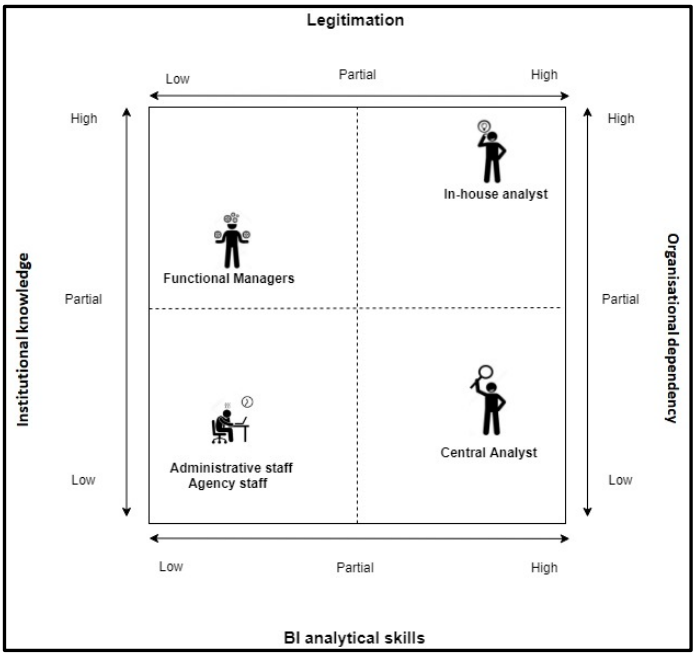


Figure 7.4: BI Power Matrix Application

Additionally, the functional managers were heavily reliant on the in-house analysts, thus also increasing their influence through this interplay of dependency. Alternatively, the central analysts, as represented in Figure 7.4 can be seen as having high analytical skills and also some degree of legitimacy, due to them being a corporate resource, reporting more towards the needs of the senior management, yet given their limited institutional knowledge and lack of organisational dependants, were unable to leverage the influence the in-house analysts were able to. Additionally, the Figure 7.4 represents the functional managers as being equipped with institutional knowledge, and also how other organisational actors may be reliant on them due to their 'process power', however, with limited analytical skills the use of BI is shifting influence and essence power away from them and to organisational actors such as the in-house analyst, who are organised below them in the hierarchy.

7.5 Conclusions

This chapter provided insights into the revised conceptual framework, discussed the propositions of this research and offered detailed discussions relating to the key findings of this research in line with the academic literature. Accordingly, the chapter presented theoretical frames of reference which encapsulated the key findings and discussions from this research. Additionally, the BI Power matrix was also developed off the back of the key findings from the previous chapter and the discussions from this chapter.

8.0 Chapter 8: Conclusion

8.1. Meeting the research aims and objectives

This research set out to answer three main research questions namely around how BI is used, its impact within a public healthcare organisation and how the use of BI can impact the organisational power dynamics between various organsational actors. Through taking a human centric approach, this research has satisfied these questions as reflected during the findings and discussions chapter of this research. As a result, this research presents a number of practical and theoretical contributions which will be discussed in more detail in

this concluding chapter. The research objective of this research have been met as highlighted in Table 8.1;

Objectives	Chapters
1) To propose an appropriate conceptual framework which will help explore how BI is used by various actors and its implications on organisational power dynamics, while also translating the research needs into research propositions	3 & 4
2) To utilise a suitable research methodology, which will assist in identifying the role of human behavioural factors and other key factors which influence BI use and impact power dynamics.	4
3) To explore the research propositions and revise the conceptual framework where required.	6 & 7
4) To offer theoretical and practical implications as well as exploring direction for future research resulting from this work.	7 & 8

Table 8.1: Research objectives mapped against thesis chapters

8.2 Practical implications

This research presents some key insights which may hold practical relevance for practitioners. The findings from this research helped identify the way in which BI is used and its subsequent impact on organisational dynamics, therefore may be of high importance to organisations aspiring to implement BI yet may not have insights into how it may impact not just the organisation but also the organisational actors. This work certainly has lessons for policymakers, not least in relation to how organisational actors, such as analysts, may benefit from influence without authority as a result of their multi-faceted skills, made up of technical and institutional knowledge. These practical implications may be particularly relevant for NHS organisations and trusts, given that this research is an embedded case study within this organisation. The fact that the NHS are transitioning towards a paperless or

paper-lite environment, and with digitisation as its key strategic vision going forward, the role of the analyst is becoming increasingly pertinent. Accordingly, the reliance on analysts within the NHS is also internally recognised. Howard et al. (2015) argues that much of the allocation of healthcare resources is dependent on high quality analysis as such with lack of defined training programs to develop this profession within the NHS can result in widespread repercussions for the NHS. Moreover, Howard et al. (2015) also argue that the decision-making within the NHS is becoming more and more complex given the ability for the organisation to collect abundance of data, as such representing the pressing need for more analysts who are able to provide quality analysis without overlooking local, contextual factors. Therefore, the findings from this research can prove highly valuable for senior policymakers within the NHS in helping to facilitate BI policy and best practice across the organisation.

This research has been successful in teasing out informal, indirect consequences and implications of BI use from a human centric perspective. Therefore, not only do the findings offer some transparency and openness relating to BI use, but also presents alternative means through which BI can be used most effectively. Through providing insights into how BI is best utilised, can offer managers support in allocating the correct resources to achieve the best result from the BI. Moreover, one of the pertinent findings of this research has high value for practice. The theme of institutional knowledge, which highlighted that operationalising analytics, void of contextual information and institutional background may lead to unsuccessful utilisation of BI. As such, the practical recommendations from this research to the NHS can be represented as the following:

- Enhance where possible in-house analysts, who operate from within the organisational environment
- The requirement of the functional managers to upskill themselves with basic analytics

- The need for hybrid managers, with managerial skills mapped against strong analytical skills
- Explore more creative ways in which analysts from the Central Informatics and Performance team interact with functional managers

The findings from this research also assist in improving the understanding of the current challenges affiliated with collaborative BI use for decision-making purposes. Additionally, the insights may be highly useful for Human Resources, as the findings explicitly reflect the types of skills required to make the BI use a success. This research also highlights that by possessing prior experience of working in a particular ward or service is also highly beneficial, as such analysts are able to apply BI more connectedly, which will assist in BI acceptance and its operationalisation by others organisational actors, such as the functional managers. This research through its enactment dimension was also able to highlight pivotal factors which reduce the overall success of BI systems, such as time and target driven constraints, which drastically minimises the ability of the data analysts to provide creative and appropriate analyses. Another practical implication that can be considered from this research relates to the configuration of roles, particularly data analysts. While this research acknowledges the pertinent need for corporate central analysts, and that it is highly unlikely for every service to their own in-house analyst across all the CGC's, there remains a need for more transparency and face to face dialogue in reducing the tensions and hostilities between the central analysts and operational staff.

While the frameworks from this research hold theoretical relevance, they may also be applied practically, as they may facilitate senior organisational managers in understanding an often rather murky, unspoken dimension of organisational dynamics. Therefore, the BI Institutional Knowledge Framework may help in guiding where best to allocate analysts, whilst the BI Power Matrix can be used as a tool which provides a holistic, yet dynamic representation of key BI organisational players. The BI Power Matrix conceptualises the relationship between BI use and Power dynamics, from context of

organisational actors. This matrix therefore can be used as a representational tool to practically assist senior managers to visibly understand the association between institutional knowledge and power dynamics.

Hybrid management may also be considered as a means through which managers may overcome this shift in power dynamics in favour of in-house analysts and in essence retain their 'process power'. The term hybrid management refers to functional managers who combine a professional background with their functional skills and responsibilities (Llewellyn 2001; Montgomery 2001). From within the healthcare context, it is previously reported that the term 'hybrid' implies the coming together of disparate logics, such as medicine and management (Edmonstone 2009; Kippist and Fitzgerald 2009). Thus, through a hybrid approach, functional managers are able to converge and manage the cross over between medicine and management. Accordingly, with the rise of analytics and the strategic aspirations within healthcare to leverage insights from data, there is an arising need for hybrid leadership in terms of embodying, translating and mediating between the fields of data analytics and management.

It is recognised that there is an increasingly greater overlap between professional and managerial activities within healthcare (Causer & Exworthy1999, Hewison 2004). It is argued that such amalgam can lead to certain advantages. For example, Spehar et al. (2014) refer to the role of the hybrid manager within healthcare, and highlight how they are able perform as 'organisational integrators' who have the ability to coordinate between senior management and front-line staff as well as across supporting services across the organisation, (Schlesinger & Oshry 1984). Repositioning this from within the context of this research, it is recognised that while not as a hybrid manager, but as an organisational actor with hybrid sets of skills, the in-house analyst is able to facilitate operational tasks whilst also being a strategic value for senior management, due to top-down up strategic vision.

The findings and discussions with the participants of this research presented a belief that by having a strong-set of analytical skills, supported by contextual background knowledge is insufficient for exerting both upwards and downwards power within the organisation. The findings reveal that the in-house analysts were increasingly gaining influence without authority, as a result of legitimacy they receive from senior management. As such, this legitimacy diminishes the power of functional managers at the lower levels of the hierarchy, thus also making the in-house analysts dominant within their environment. Furthermore, the in-house analyst was also able to exert downwards power over the clinicians, due to their ability of analysing clinical performances, not only from an analytical point, but also from a localised, contextual perspective, thus making the in-house analyst a highly influential organisational actor embedded within the environment.

8.3 Theoretical implications

A number of key theoretical implications are generated as a result of this research, through: (1) the appreciation of the BI related dissonance between various organisational actors (2) insights into power dynamics resulting from BI use (3) an understanding of the fundamental role of institutional knowledge. Through exploring the extant literature, this research identifies a lack of BI studies which places emphasis on the human agency and its role in the use of BI, this was a result of studies being focused on technical architecture and more technical factors. However, in building on existing stream of literature this research further to the direction laid by Shollo and Galliers (2016), by not only taking the human centric approach at exploring BI, but by also exploring the role of BI in impacting organisational power dynamics.

8.3.1 Uncovering health power dynamics

In sum, this study contributes to the growing body of work in the IS field which examines IT in health care Currie (2012). Additionally, this work essentially

answered the call of Pouloudi et al. (2016), by exploring conflicted views and perceptions amongst individual stakeholders, thus highlighting the impact such conflict may have on public sector IT/IS programmes. Furthermore, this research also contributes to healthcare literature, which, while having focused on human agency and decision-making, has been largely from a Management-Clinician dyad, as opposed to from a Management-Analyst dyad. Additionally, the extant literature within healthcare research has explored decision-making from intuitive and analytical approaches, this has largely been overlooked from within healthcare management literature. As such, this research contributes further by outlining the role of intuitive and analytical decision-making approaches within the healthcare sector, but more importantly provides pertinent insights into the rationale behind why certain organisational actors may opt for a particular approach from within this decision-making dichotomy. Theoretically, this work also broadens the Enactment theory through applying power dynamics to a complex NHS organization to interpret the empirical data on BI use within the NHS.

8.3.2 IS and Power dynamics

Moreover, synthesising the literature illustrates studies exploring power dynamics from an IS context was an understudied phenomenon, while it was apparent that some studies have explored the impact of technology on intra-organisational dynamics (Pettigrew 1973; Markus 1983), this largely been overlooked from within more recent forms of IS, such as BI. This research also proposes several theoretical contributions. For instance, the ‘BI Power Enactment Framework’ proposed in this research was built on existing theory, through combining various theoretical constructs and extending earlier works on enactment theory (Orlikwoski 2000) and merging it with the sources of organisational power (Hardy 1993), to create a sense tool which helps establish how the use of BI may impact various aspects of organisational power. As such, it is argued that this framework provides appropriate lens for exploring technology related power dynamics, particularly as the findings and

insights from this research highlight how certain actors are able to become increasingly influential within their environmental settings. Additionally, as a result of the findings, this research also proposes the 'BI Power Enactment Framework' which may be used by researchers as sensemaking lenses and a guide to further explore the role of power dynamics resulting from BI or data analytics use within an organisation.

8.3.3 BI Power Enactment Framework

This research also extends the TEF through incorporating it with other theoretical constructs to uncover impact of power, thus this research contributes the '*BI Power Enactment Framework'* which can also be applied by researchers as a guide to explore power dynamics resulting from the use of socio-technical systems, which requires human decision-making. This framework firstly acknowledges environmental factors along with cognitive, human factors which may affect how a technology may be used. By acknowledging the impact of such factors in addition to institutional knowledge can offer researchers with appropriate sense making lenses to explore the power dynamics resulting from technology use.

8.3.4 BI Power matrix

Another key contribution of this research is in form of the 'BI Power matrix' which can be used as a guide to help senior management to establish the extent to which the use of technology plays a role in impacting dynamics within the organisation. All these contributions have in common the fact that they are theoretical contributions, which explore technology use from an socio-technical perspective, thus providing an array of opportunities for future researchers to implement these frameworks in further studies looking to explore the Technology-Power dyad. Through highlighting the important role of institutional knowledge, this research extends knowledge work from within the IS field, namely by enhancing the insights into knowledge creation through BI systems, recently unlocked by Shollo and Galliers (2016). This research

also answers the call of Sharma et al. (2014) who highlighted a lack of insights into how managers use BI and data analytics for creating actionable insights. Through the guidance of BI Power Enactment framework, this research was able to fulfil this void by providing both empirical and conceptual insights into the use of BI, and its subsequent consequences on intra-organisational dynamics.

8.4 Lessons learnt from the NHS case study

The case study demonstrates the implications of BI use within a healthcare, public sector settings, and specifically uncovers its impact on organisational power dynamics. A key challenge for the NHS is successfully managing large scale IT / IS projects, given its large complex nature, fragmentation, intra-organisational dynamics and bureaucratic tendencies. For instance, attempting to achieve standardisation across an organisation such as the NHS, which employs approximately 1.5 million people across the UK is a mammoth task. However the tentative lessons outlined below represent an extrapolation of the key lessons learnt from the case study and can guide researchers and practitioners towards better understanding of applying BI tools in a public sector context:

• Lesson 1: Organisations that want to undertake large scale BI projects should provide substantial analytics training to operational managers, regardless of their background. Possessing non-technical skills and having the ability to understand how to interpret data is sufficient in minimising tensions between management and analysts

• Lesson 2: Analysts who operate within the department they produce insights for, can generate more meaningful insights than those who operate remotely

• Lesson 3: In an increasingly data-driven environment, data analysts are emerging as influential and valued organisational actors, thus having the ability to shift power dynamics

• Lesson 4: Managers still largely practice intuitive-decision making and rely on their ‘gut-feeling’ whilst overlooking data if it suits their interests

• Lesson 5: The strict hierarchical and political nature of public sector organisations creates an unwillingness from organisational staff to engage and participate in top-down driven initiatives, therefore this must also be overcome to ensure the successful implementation of BI

• Lesson 6: Given the dynamic and complex nature of public sector organiations, it is imperative to conduct a pilot study prior to partaking a case study research, as this will assist in uncovering dynamics and issues not previously acknowledged, whilst also helping to improve the interview protocol.

8.5 Limitations of this research

As with many studies, this research also has some limitations. It is acknowledged that the single case study does not allow for broader, statistical generalisation. While this approach provided an in-depth account of the phenomenon in question and covered important issues relating to the role of BI in impacting power dynamics between organisational actors, further investigations are required to evaluate the wider implications of the BI-Power dyad. Therefore, the lack of comparative power can be seen as a limitation of this research. Furthermore, the research sample was largely made up of functional managers and data analysts, however the clinicians were largely omitted from the research sample as they were not direct users of BI systems. However, given that much BI reporting relates to the performance of clinicians, it may be worthwhile also including this group of organisational actors in future studies, thus exploring the impact of BI on healthcare clinicians.

8.6 Future direction

Owing to the exploratory scope of this research, the findings from this research, offer the potential for further research. Exploratory case studies are often a prelude to further studies, which in this case can assist in offering more insights into the role of technology in impacting power dynamics within organisations. Accordingly, the key findings of this research and particularly the developed framework can be applied to other NHS trusts in order to gauge whether similar instances of power dynamics resulting from BI use are prevalent across the entire organisation. Furthermore, the findings from this research may also be useful in comparing NHS trusts with differing degree of BI use, thus through the application of the BI Power Matrix may offer significant insights into influential organisational actors across NHS trusts which have high as well as low degree of BI use. More broadly, it is argued that the key dimensions of the BI Power Enactment Framework can be analytically generalised and be applied in other contexts, such as different healthcare sectors or industries. The framework essentially incorporates key elements, such as human decision-making factors, technology enactment, Institutional knowledge and power dynamics. Therefore, the framework can be applied in order to explore power dynamics resulting from Human-Technology interactions, regardless of the type of technology. Therefore, it is argued that this framework can be applied to explore other technological advancements too, such as AI and Industry 4.0 as the essence and focus of the framework remains valid and relevant regardless.

As also highlighted as a limitation, although this study focused on the role of BI exercised power dynamics between organisational actors, this was largely between the functional managers and data analysts. However, clinicians are a large and pertinent group within healthcare and are also seen to be impacted by the use of BI in this research. Consequently, future research may be directed at exploring how the use of BI impacts clinicians, particularly given the fact that much of the BI output and reporting is in relation to clinician performances. Healthcare literature has largely focused on the Management-Clinician dyad, however future research may explore the Analyst-Clinician dyad, particularly given that this research highlights that analysts were able to

exert pressure downwards, towards clinical and administrative organisational actors.

This therefore would offer insights into BI from professional organisational actors, who possess a particular expertise, as opposed to from an expertise / functional perspective. Furthermore, while this research explored the impact of BI amongst organisational actors, it may be argued that the role of other technologies in impacting power dynamics is also a timely and relevant topic of discussion. More recent trends such as industry 4.0, artificial intelligence, and robotics are having profound impact across various contexts. Therefore, by adapting the theoretical frameworks proposing this research may help tease out issues of conflict and the shift of power resulting from these technological advancements.

Moreover, as a result of the findings and discussions, this research further recommends further research into areas which were either not completely explored or remained untapped. Accordingly, the following research propositions may be explored in future research:

Proposition 1:

The role of BI impacts power dynamics between clinicians and Data analysts, whereby the data analysts are more influential.

Proposition 2:

In the absence of time and target pressures, the corporate central data analysts, are able to perform a better service for functional managers.

Proposition 3:

The role of Institutional Knowledge and Analytical skills is not always the pre-requisite for attaining organisational influence.

Proposition 4:

Hybrid leadership, through managers possessing analytical skills can renegotiating the power shift from data analysts, back to functional managers.

Overall, this research has addressed the knowledge gaps through building on existing BI literature by taking a human focus, in doing so this research offers empirical and theoretical contributions to BI and healthcare literature, as well as Power literature. Furthermore, this study has also uncovered direction for further research, thus offering research avenues which can help advance these fields of scholarly research. The practical implications from this research can assist policy makers, particularly in the public sector, to minimise disruption resulting from the implementation of technology initiatives.

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APPENDICES

APPENDIX A – Research Information Sheet

Dear prospective participant,

Business Intelligence (BI) is still largely observed from its technological origins in academic literature. However, it is gradually expanding to cover beyond its traditionally technical focus towards non-technical elements, such as the users of these technologies. Therefore, this research as part of a PhD degree at the University of Bradford addresses limitations of current research and focuses on the users of BI, exploring how BI systems are used by various users for decision making purposes. Specifically, the research will aim to achieve an insight into the impact of BI use upon its various users.

Your contribution: In order for me to gain an understanding of the context in which BI is used, and how it assists in decision making, I will be required to conduct face to face interviews (semi-structured) with various BI users, partake in observations and also review documentation. I welcome data analysts, decision making managers and other users of BI in the organisation. If you agree to participate in this research, you will be asked questions regarding your use of BI, how you perceive these technologies impact your work and influence the decisions you make. The interviews will take a maximum of 45 – 60 minutes of your time. For analysis purposes, the interviews will be recorded and transcribed into written notes. Please let me know if you object to the interview being recorded.

Feedback: As a participant of this research, I will provide you with the transcript of the interview (or written notes of the interview, if you refuse to be audio recorded) upon completion. This will provide you with the opportunity to confirm accuracy, allow for any clarifications or corrections, and to verify anonymity. You will also have the choice to receive the report of the completed research. I will not send you any further information, unless I am requested to do so by you.

Confidentiality and anonymity: As a researcher, it is my duty to maintain confidentiality and anonymity at all times. The confidentiality of the interview will be assured. Upon completing this research, all the documents and tapes will be stored in an electrical format in the University of Bradford's digital research repository, which is secure, and password protected. Furthermore, any conference or journal publications connected with this research will not be attributable to individuals.

Potential of risk: There are no risks to you in taking part outside of those you would experience in everyday life. However, by taking part, if you recall things that may distress you, the researcher will ask you whether you want to continue participating in the interview. Any decision you make will be

respected. The contact details of the principal supervisor will be provided if there is anything further you would like to discuss. Alternatively, I can also offer to provide you with a list of local contacts (e.g., counselling services) that are not part of the research team if you would like them.

Voluntary participation: Your involvement in this research is on a voluntary basis, therefore as a participant you hold the right to withdraw your consent and stop participation during any stage of the research up until commencement of data analysis. You may also choose not to respond to any questions put forward during the interview.

University approval: This research has been approved by the University of Bradford Ethics committee.

Contacts: If you require addition information, or have any concerns relating to this proposed research, please contact me on +447506 775928 or alternatively at k.a.mahroof@bradford.ac.uk. You may also contact my supervisor Dr Zahid Hussain at z.i.hussain@bradford.ac.uk.

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I would really welcome your participation and contributions to this research project. If you agree to being interviewed and are prepared to participate, please complete and sign the informed consent form.

Thank you for your time.

Kamran Mahroof

APPENDIX B – Research consent form

Informed consent form

This informed consent form requires for it to be signed by each research participant, and kept on record by the researcher.

1. Title of research project**:** A study exploring to what extent the use of Business Intelligence (BI) impacts its users.

2. I, ……, hereby voluntarily grant my permission for participation in the project as explained to me by *Kamran Mahroof*.

3. I have been informed of and understand the purposes of the study. The nature, objective, possible safety and health implications have been explained to me and I understand them.

4. I have been given an opportunity to ask questions and been provided with the appropriate contact details to do so.

5. I understand my right to participate voluntarily in this research and am aware that information will be handled confidentially. I understand the results of the research will be published but will not be not be attributable to individuals.

6. I agree to participate in this study as outlined to me and understand I can withdraw at any time up/until commencement of data analysis, without giving any reason. Upon signature of this form, you will be provided with a copy. You may also keep the accompanying information sheet.

Signed: _____ Date: _____

Thank you for willing to participate in this study. If you are interested in receiving
the aggregated results of this research please provide the e-mail address to which it
can be sent: …….

7. I certify that I have explained to the above individual the nature and purpose of this research study, have answered any questions and have witnessed the above
signature.

Researcher: _____ Date: _____

APPENDIX C – Interview Guide

Introduction of the researcher

Brief overview of the research project

Part 1 – Participant Demographic Information

- Participant Name / Initials:
- Title:
- Profession:
- Background:
- Age:
- Time in the current position (Years):
- Outline of work duties and responsibilities:

Part 2 – Human behavioural factors

- What types of decisions do you get involved with?
- Who else uses BI within your organisation?
- Can you please discuss a recent decision-making event in your role?
- What factors do you consider when you make decisions?
- Does your role involve the use of Business Intelligence? If yes, please elaborate how you use it?
- Does personal intuition play a part when you make BI driven decisions? If yes, please elaborate how?
- To what extent do your skills influence your use of BI? Please elaborate
- Do you think individual's personalities affects how you use BI? If yes, please elaborate how?
- Does this impact the relationship between colleagues?

Part 3: Environmental factors

- How would you describe the environment you work in?

- Which of these factors do you feel impacts your decision-making?
- Do these environmental factors influence the way in which you use BI?
- If these factors were not present, what would be different?
- Do you have target pressures in your role? How much does this influence the way you work?
- How would you describe your interactions with colleagues from other departments?

Part 4: Technology-Human interaction

- How do you apply Business Intelligence in your daily work?
- In what ways do you use Business Intelligence? Does it differ when compared to other colleagues?
- Do you feel the way in which you use Business Intelligence impacts your relationship with your colleagues? If so, please elaborate.
- To what extent do the factors you highlighted earlier influence the way you use Business Intelligence?

Part 5: Articulation

- Can you describe in your own words what you consider is a decision making process? Can you provide any examples?
- Does any articulation occur between colleagues during or after this process? If so, between who?
- What occurs after BI reports are generated? Who are the key actors during this process?
  What is the nature of these discussions?
- Are there any dominant actors during this process? If so who and why?

Part 6: Power dynamics

- How would you define power in the workplace?

- Do you feel that having expertise and skills relating to Business Intelligence make one more influential in this place?
- Has NHS's focus on Business Intelligence affected the influence held by managers? Please elaborate
- Do certain groups have more influence and power than others as a result of the use of Business Intelligence?
- How would you define power in the workplace?
- Would you say there is a connection between the environmental factors you discussed earlier and power?
- Do you think the behavioural factors discussed earlier impacts power?

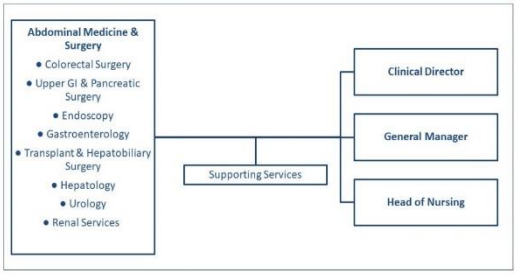
APPENDIX D - Relationship of research propositions and interview protocol

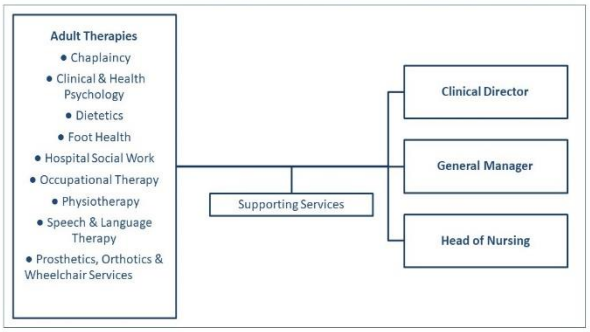
Propositions	Corresponding Interview Question
P1: Human behavioural factors influence the way in which BI is enacted and used by organisational actors	• Does personal intuition play a part when you make decisions? If yes, please elaborate how? • To what extent do your skills play a part in how you make decisions? • Do you think individuals personalities affects how you make decisions? • What factors do you consider when you make decisions? • Does this impact the relationship between colleagues?
P2: Environmental factors influence the way in which BI is enacted and used by various organisational actors	• Which of these factors do you feel impacts your decision-making? • Do these environmental factors influence the way in which you use BI? • If these factors were not present, what would be different in your use of BI? • Do you have target pressures in your role? How much does this influence the way you work? • How would you describe your interactions with colleagues from other departments?
P3: The way in which BI is enacted by organisational actors impacts BI	• Do you feel the way in which you use Business Intelligence impacts your relationship with your colleagues? If so, please elaborate.

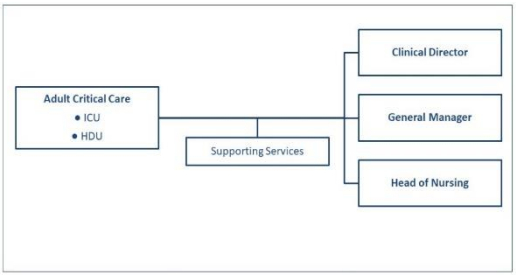
articulation and the BI decision-making process	• In what ways do you use Business Intelligence? Does it differ when compared to other colleagues? • To what extent do the factors you highlighted earlier influence the way you use Business Intelligence? • How important is it for you to discuss Business Intelligence analysis with other colleagues?
P4: Data articulation occurs between various organsational actors during BI decision-making	• Can you describe in your own words what is for you a decision making process? Can you provide any examples? • Does any articulation occur between colleagues during or after this process? If so, between who? • What occurs after BI reports are generated? Who are the key actors during this process? • What is the nature of these discussions? • Are there any dominant actors during this process? If so who and why?
P5: The use and BI technology enactment by organisational actors within the NHS is bringing about a shift in power dynamics through 'Resource, Meaning	• How would you define power in the workplace? • Do you feel that having expertise and skills relating to Business Intelligence makes one more influential in this place?

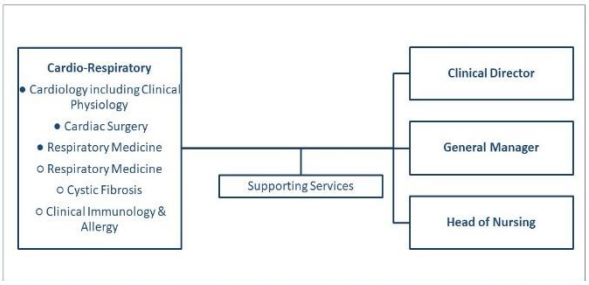
and/or Process' power dimensions.	• Has the focus on Business Intelligence affected the influence held by managers? Please elaborate • Do certain groups have more influence and power than others as a result of the use of Business Intelligence?
P6: Environmental and behaviour factors also has an indirect impact on power dynamics between various actors	• Would you say there is a connection between the environmental factors you discussed earlier and power? • Do you think the behavioural factors discussed earlier impacts power? •

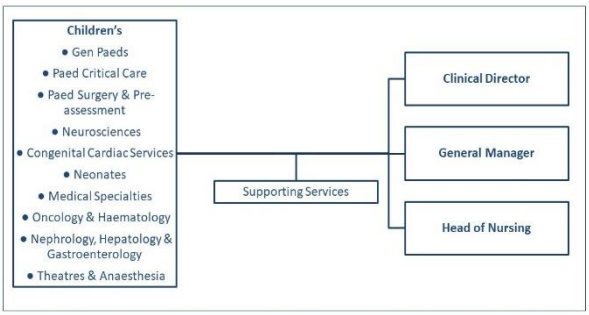
APPENDIX E – Trust CCU Breakdown

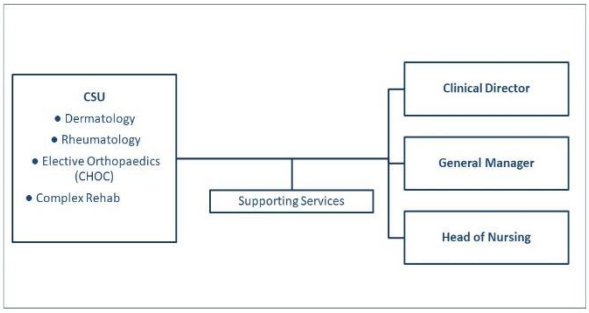


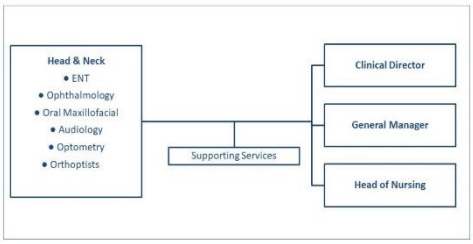


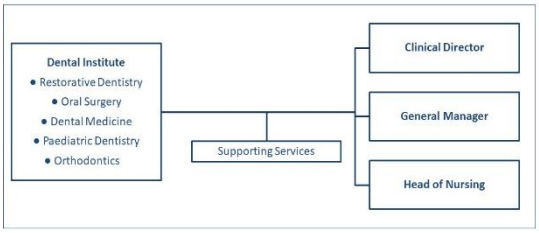


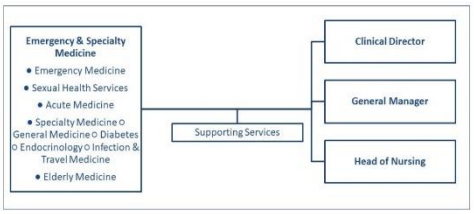


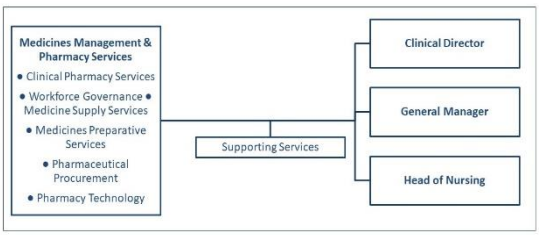


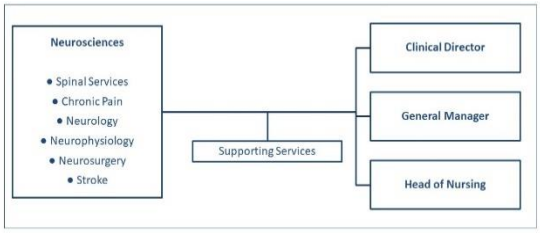


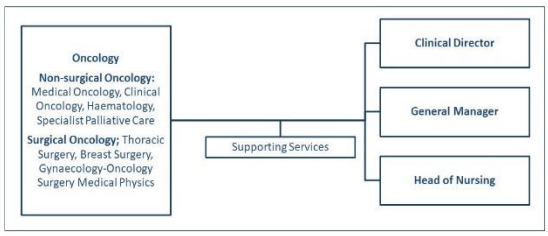


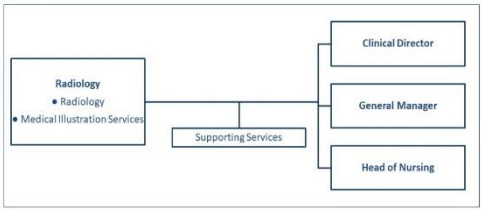


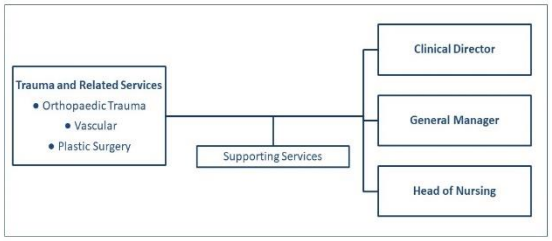


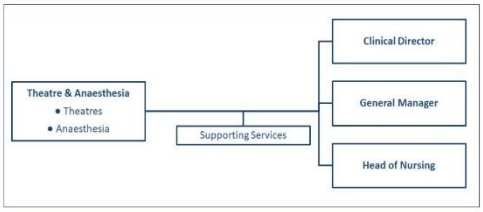


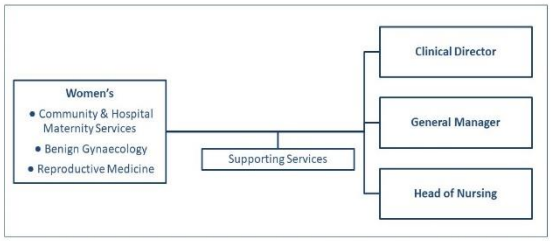


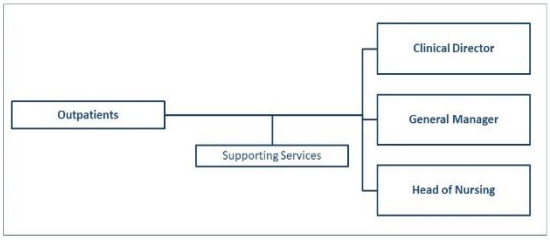


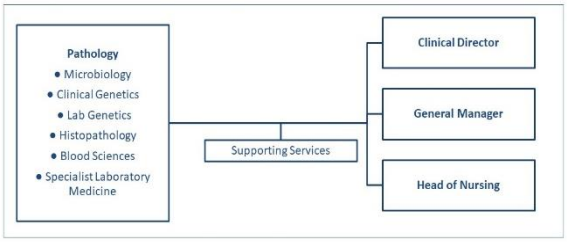

Radiology
• Radiology
• Medical Illustration Services
Supporting Services
Clinical Director
General Manager
Head of Nursing


Trauma and Related Services
• Orthopaedic Trauma
• Vascular
• Plastic Surgery
Supporting Services
Clinical Director
General Manager
Head of Nursing


Theatre & Anaesthesia
• Theatres
• Anaesthesia
Supporting Services
Clinical Director
General Manager
Head of Nursing


Women's
• Community & Hospital Maternity Services
• Benign Gynaecology
• Reproductive Medicine
Supporting Services
Clinical Director
General Manager
Head of Nursing


Outpatients
Supporting Services
Clinical Director
General Manager
Head of Nursing


Pathology
• Microbiology
• Clinical Genetics
• Lab Genetics
• Histopathology
• Blood Sciences
• Specialist Laboratory Medicine
Supporting Services
Clinical Director
General Manager
Head of Nursing